Male Earnings Dispersion Over the Period 1973 to 1995 in Four Industries

Thesis

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Male earnings dispersion over the period 1973 to 1995 in four industries

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Abstract

The following looks at developments in male earnings dispersion in four UK industries over the period 1973 to 1995. Evidence to date in the UK is largely based at the economy-wide level only, or aggregated into manufacturing and non manufacturing sectors. By considering industries other than solely manufacturing it is possible that different trends have occurred in earnings dispersion for each industry. The main objective is to firstly split earnings dispersion over the 23 years into two components: between-group earnings dispersion which occurs as a result of differing worker characteristics across the population; and within-group earnings dispersion, that is any remaining dispersion after controlling for measurable worker characteristics. And secondly, potential factors able to explain within-group earnings dispersion in each industry are tested, namely technological change; globalisation; female participation; immigration and institutional change. The empirical methodology is two step in nature. Initially, micro data based upon the individual is used to purge dispersion of human capital and personal influences. Then, time series techniques are employed to analyse the trend in the measure of within-group dispersion and the potential causal factors.

The results from the first step indicate that whilst within-group earnings dispersion dominates between-group earnings dispersion trends differed across each industry. In line with previous results at the aggregate level, it appears that relative demand shifted in favour of the higher skill endowed. The second stage results indicate that whilst technological shocks are significant in each industry, other factors have a role to play in particular globalisation and supply side influences. A time series analysis of the explainable part of the earnings distribution i.e. between-group earnings dispersion shows that this too was influenced by market forces and institutional change. Furthermore, the returns to education were influenced by technological change and globalisation.

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Introduction and Overview

1.1 Background information on the trend in earnings dispersion

Over the past two decades the gap between the richest and poorest members of society has widened (Goodman, Johnson and Webb, 1997). Earnings are an important part of overall income and the trend in the dispersion of earnings closely follows the trend in the dispersion of overall income (Gosling, Machin and Meghir, 1996). Previous research has shown that earnings dispersion fell during the 1970s, only to increase rapidly during the 1980s (Schmitt, 1995).

Part of the change in earnings dispersion can be related to changing returns to labour market skills, such as education and experience. It is possible to disaggregate earnings dispersion into **between-group** and **within-group** components. Between-group dispersion accounts for earnings dispersion arising due to different levels of characteristics amongst individuals. For example, between the young and old, the highly educated and the school leaver with minimal qualifications, low-experienced and high-experienced individuals, whites and non-whites, regional pay variations and wage differentials between industries. The sharp rise in earnings dispersion between education and experience groups manifests itself in the substantial growth in the financial returns to education and experience that took place in Britain during the 1980s (Schmitt, 1995). However, earnings dispersion has also increased within specific groups defined by characteristics such as age, education, experience, colour, region and industry. Over the past two decades between-group effects have explained only a portion of the overall rise in earnings inequality. Schmitt (1995) found that education and experience could only account for 40 per cent of the rise in earnings dispersion during the 1980s, with 60 per cent occurring within education and experience groups. Similarly, Machin (1996[a]) showed that a significant portion of the overall rise in earnings dispersion remains unexplained by rising returns to age and education. Moreover, dispersion occurring within age, experience groups increased by 23 per cent from 1979 to 1993 (Machin, 1996[a]).

The majority of the trend in increasing earnings dispersion is as a result of a widening distribution of earnings occurring within-groups of workers possessing similar experience and educational characteristics (Schmitt, 1995; Machin, 1996[a]). Any explanation of rising earnings dispersion must be capable of accounting for these within-group changes. A shift in the relative labour demand in favour of workers with high levels of skills appears to be the most likely explanation (Levy and Murnane, 1992; Gosling, Machin and Meghir, 1996)[1]. This increase in earnings dispersion occurring within narrowly defined groups has been related to several factors, including changes in demand and supply patterns for labour, and the influence of pay-setting institutions. To the extent that unions have maintained reasonable levels of pay by creating wage floors above the market clearing level, a marked decline in collective bargaining can be expected to have influenced earnings dispersion.

[1] Whilst the literature on earnings dispersion has focused largely upon an increase in the demand for higher skilled workers as being the cause for rising earnings dispersion – even once controls for educational attainment have been implemented, other factors may also be at work which operate outside of the competitive demand and supply framework usually adopted. For instance organisational change, efficiency wage and insider-outsider models, each of which could potentially offer alternative explanations of the observed increase in the earnings of higher skilled workers. These other influences upon earnings are discussed further in Chapter Two, section 2.5.

The increased globalisation of the world economy has been suggested as a reason for increasing within-group earnings dispersion in the United Kingdom and the United States (Murphy and Welch, 1992). Investment is now far more mobile than ever before, and is thus able to respond to cross country differences in unit wage costs. In particular, to maintain their competitive position firms facing international competition are under pressure to keep unit costs down. It has been suggested that, because wage costs differ greatly between the developed world and less developed countries, firms have an incentive to take advantage of low wage costs by specialising in skill-intensive production, and contracting out low skill-intensive production to countries with low unit wage costs (Wood, 1994). Consequently, the demand for lower skilled workers would decline, creating a gulf between the earnings of the high and low skilled.

Others have argued that technological change has increased the relative productivity of high- versus low-skilled workers (Bound and Johnson, 1992; Machin, 1996[a,b]). Examples of this are the introduction of computers into the workplace and machines completing assembly tasks previously done by low-skilled workers. This has resulted in an increase in the demand for workers possessing good skills, and is in contrast to the technological changes implemented earlier this century and during the industrial revolution, which required low-skilled labour (Goldin and Katz, 1996).

Less common explanations apparent in the literature which focus on market forces are the role of female participation and immigration. Both of these factors may increase the supply of relatively low-skilled labour, and thus may drive down the wages of low-skilled workers. The impact of both changing female participation rates, and immigration is largely dependent upon the degree of substitutability. For example, if females or immigrants are substitutes for low-skilled workers, then a rise in the supply of either leads to a fall in the demand for the lower skilled and consequently a decrease in their wages (Topel, 1997).

Aside from market force explanations, other authors have stressed the importance of labour market institutions, in particular trade unions, in shaping the way labour markets have responded to these changes in demand and supply (Freeman, 1993; Gregg and Machin, 1994). Market force explanations can explain many of the similarities in the development of the wage structure, but are less illuminating when attempting to explain differences (Gottschalk and Smeeding, 1993, 1997). Most economies have been subjected to increased technological change and globalisation, yet only the United Kingdom and the United States experienced substantial increases in earnings dispersion (Katz, Loveman and Blanchflower, 1995). Further, recent evidence has indicated that those countries with lower levels of centralised bargaining, in particular the United States and the United Kingdom, have experienced widening earnings dispersion (Teulings and Hartog, 1998).

1.2 The contribution made by this study

The primary objective of this study is to examine developments in the British wage structure over the period 1973 to 1995. Evidence to date on earnings dispersion has either been based on the economy as a whole (Schmitt, 1995) or for manufacturing industries (Machin, 1996[a,b]). This study focuses upon four industries : these are Manufacturing, Other Manufacturing, Construction and Transport & Communication. Of particular interest is assessing whether the four industries experienced the same trends in earnings dispersion. By considering specific industries outside of the manufacturing sector, it is possible that different factors may have played a significant role in each industry. For instance, the role of female participation and the supply of immigrants - supply side pressures may be of greater importance than demand influences (technological change and globalisation) in certain industries. Also factors contrary to the market mechanism may also be at work, specifically declining collective bargaining as unionisation falls.

An innovative approach of this study is the two stage empirical approach adopted to analyse earnings dispersion. Initially, repeated cross sections of the annual General Household Survey over a period of 23 years are used to control for differences in earnings. Earnings differentials which may arise between individuals can stem from experience, education, colour and region, all of which may affect earnings. This enables earnings dispersion to be split into between-group and within-group components, following Schmitt (1995) and Machin (1996[a,b]). The between-group component is explained by the data available from the General Household Survey and arises due to changing returns to individual characteristics. Of potentially greater importance is the trend in within-group earnings dispersion over the 23 years. In the second stage, time series analysis considers the role of globalisation, technological change, female participation, immigration and labour market institutions. Of particular interest is how each may have influenced the trend in within-group earnings dispersion over time in each of the four industries considered. The time series method used is cointegration, which allows the analysis of within-group earnings dispersion and the themes dominant in the literature. It is possible that over the 23 years some of the variables (within-group earnings dispersion, globalisation, technological change, female participation, immigration and labour market institutions) may trend up or down in a non-stationary fashion, and groups of variables may drift together. If there is a tendency for some linear relationships to hold over the 23 years between within-group earnings dispersion and its potential causes, then cointegration analysis helps to discover this.

A two stage empirical methodology is deemed preferable to alternatives for a number of reasons. First, there would be problems of pooling the data over time, because data based upon individuals is used along with more aggregate industry level data. Consequently, pooling could result in aggregation bias where estimates are downwardly biased (Moulton, 1986). Second, there is a possibility that the industry level data may be non-stationary over time. This presents a major problem, in that data pooling without considering the stationarity of the variables can result in a spurious correlation. The two stage approach draws together different strands in the literature. Previously, earnings dispersion has been decomposed into between-group and within-group dispersion using individual data (Juhn, Murphy and Pierce, 1993; Schmitt, 1995; Machin, 1996[a]). Time series methods have been used to study the potential causes of earnings dispersion over time (Borjas and Ramey, 1994; Buckberg and Thomas, 1996; Leslie and Pu, 1995), but only at the economy-wide level and not for a measure of earnings dispersion purged from differing returns to worker characteristics. The empirical approach used in this study combines these two approaches. First, to purge earnings dispersion of differing distributions of education, experience and personal characteristics across the population, all of which may affect the trend in earnings dispersion. Second, to avoid the problems of aggregation bias and examine the major contributor to within-group earnings dispersion, for each industry.

Research to date has only offered snapshots for particular years[2], rather than forming a consistent time series of within-group earnings dispersion.

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[2] In particular, Schmitt (1995, pp.182, Table 5.2) focuses upon three periods of time, 1974–76, 1978–80 and 1986–88, considering changes between each snapshot, rather than the overall trend in within-group earnings dispersion. Similarly, Machin (1996[a], pp.56, Table 7) considers five snapshots : 1979, 1982, 1986, 1990 and 1993.

Whilst snapshots allow the analysis of earnings dispersion between two static periods of time, they are less informative about the trend of earnings dispersion over time. In the absence of large scale, long term panel data sets, repeated cross sections offer the best insight available, into the structural changes that have occurred in the British labour market over the last two decades. The repeated use of cross sections introduces an element of time series variation, into otherwise conventional cross sections.

1.3 Overview of the thesis structure

This study focuses solely upon the evolution of male earnings over time. The reason for this is that females may enter and exit the labour market to have children, a decision which can be influenced by earnings. Consequently, any such decision leads to modelling problems and also the earnings of females may be subject to discontinuities over time.

Chapter Two introduces the different theoretical explanations which may have caused an increase in earnings dispersion, over and above that due to differing returns arising from worker characteristics. Possible explanations consist of the impact of market forces as they change over time and institutional changes. It is important to have an understanding of such factors, as the empirical approach adopted in this thesis attempts to see which had the largest impact on dispersion over the period 1973 to 1995. Chapter Three discusses the empirical methodologies adopted, to test the dominant theories in the literature as introduced in Chapter Two. Problems with the empirical methods previously used are also considered in Chapter Three. Chapters Two and Three are used to review the theory and empirical practices adopted, to assess the possible causes of rising dispersion.

Chapter Four outlines the methodology used in this analysis, stemming from previous applied work in the area, in order to test the competing theories grounded in the literature. The methodology used in the first stage of the empirical procedure, to split earnings dispersion into between-group and within-group components, is introduced, along with the time series methodology of the second stage which tests the competing theories. In Chapter Five the data used in the two stages is introduced. This consists of individual level data to decompose earnings in the first stage of the empirical approach, and industry level data to proxy the themes dominant in the literature used in the second stage of the empirical testing. Problems associated with data collection are discussed here and the method of obtaining consistent industry level data is outlined.

The empirical results derived from the application of the two stage approach are given in Chapters Six and Seven. Chapter Six shows the results of disaggregating earnings dispersion into between-group and within-group components for each industry. Simple plots of the data show whether the four industries experienced the same trends in between-group and within-group earnings dispersion. Tests of the robustness of the first stage results are also discussed here. Chapter Seven tests the competing theories together, by time series analysis over the past two decades. Results for each industry are obtained and compared to see whether the same factors (globalisation, technological change, female participation, immigration and labour market institutions) have played a significant role in shaping within-group earnings dispersion, for each industry. Finally, Chapter Eight summarises the findings, discussing how the results differ with previous research and looking at any policy implications.

2

A Literature Review of the Theoretical Concepts Behind Earnings Dispersion

2.1 Introduction

The purpose of this chapter is to introduce the factors that have the potential to explain within-group earnings dispersion, in other words earnings dispersion after controls have been made for the influence of worker characteristics. There are a number of possible explanations for rising within-group earnings dispersion. In particular it is possible to identify changes that are due to market forces and those reflecting institutional change, where the former suggests that earnings dispersion arises due to demand and supply changes. Section 2.2 considers a simple demand and supply framework to examine the evolution of relative wages in recent years. The role of market forces and institutional changes are discussed in sections 2.3 and 2.4 respectively. In section 2.5 influences upon earnings dispersion which operate outside of the competitive labour market framework are discussed. A model of the labour market is developed in section 2.6 which is able to explain the expected outcome on relative wages from the influence of the market forces and institutional changes considered in sections 2.3 and 2.4. Finally, section 2.7 concludes.

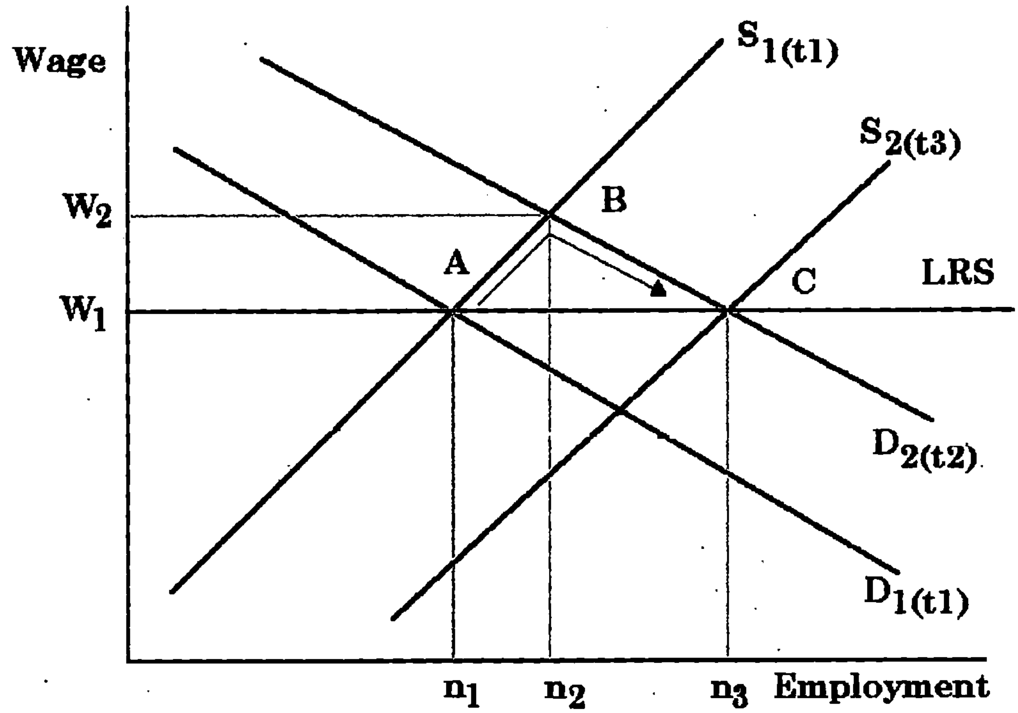
2.2 A demand and supply analysis

For the United Kingdom and the United States it appears that a large part of the increased inequality between the skilled and less-skilled can be accounted for by shifts in the relative demand for skilled workers. During the 1980s demand rose at a faster rate for workers at the high end of the skill distribution (Schmitt, 1993; Johnson, 1997). Consequently, the relative wages of skilled individuals increased. This occurrence can be shown by simple demand and supply analysis. Provided that the skilled and unskilled workers are not perfect substitutes the demand curve will be downward sloping, as is assumed in Figure 2.1, below. The vertical axis depicts the relative wage of the skilled to unskilled and the horizontal axis shows the relative employment levels of the skilled to unskilled. Initially the equilibrium is at point A in time period t_1, giving a relative wage of W_1 and relative employment n_1. Consider an increase in the relative demand for skilled labour in the second period t_2 (possible causes are discussed below). The demand curve shifts outwards from D_1 to D_2, reaching a new equilibrium at point B, yielding a higher relative wage for the skilled of W_2 and greater relative employment n_2. This story can also be expressed algebraically, where, as before, W is the relative wage between the two groups and its growth over time is given as $\frac{\partial W}{\partial t}$:

$$\frac{\partial W}{\partial t} = \frac{1}{\sigma}\left[\frac{\partial Z}{\partial t} - \frac{\partial S}{\partial t}\right] \quad \sigma>1$$

S is a measure of the relative supply of skilled labour to unskilled labour, where $\frac{\partial S}{\partial t}$ is its growth over time.

Figure 2.1 The relative demand and supply of skilled to unskilled workers



The parameter Z reflects relative demand, and the fact $\frac{\partial Z}{\partial t} > 0$ shows the relative demand curve to be shifting to the right over time, as depicted in Figure 2.1, above. The elasticity of substitution between the skilled and unskilled is denoted as σ and is assumed to be greater than unity (Hamermesh, 1993). The exposition thus far has shown increasing relative wages as a result of increasing demand. In the context of the above equation this means $\frac{\partial Z}{\partial t} \rangle \frac{\partial S}{\partial t}$, that is, the rise in demand is outpacing the corresponding increase in supply of skilled labour (in the context of Figure 2.1, $\frac{\partial S}{\partial t|t_1 \ldots t_2} = 0$, i.e. supply is constant in the first two periods). In order to bring the relative wage back to its initial level a large increase in the relative supply of skilled labour is required. Assuming this occurs in the third time period, t_3, this would lead to a shift in supply, S_1 to S_2, and the equilibrium would shift from B to C, causing wages to fall back to their initial level W_1. Under the above scenario over the time period t_1 to t_3, the long run supply curve is perfectly elastic at LRS with a wage of W_1. Consequently, from t_1 to t_3 $\frac{\partial Z}{\partial t|t_1 \ldots t_3} = \frac{\partial S}{\partial t|t_1 \ldots t_3}$, and so relative demand changes are of equal size to relative supply changes. The only difference in the labour market from period t_1 at point A is that relative employment is higher, at n_3. The above scenario has shown how rising relative demand can result in higher wages for the skilled relative to the unskilled. Moreover, to return wages to their initial level a corresponding adjustment to relative supply is required. Although the supply of skilled labour has risen over the 1980s, it has not kept pace with demand and so $\frac{\partial Z}{\partial t} \rangle \frac{\partial S}{\partial t}$, that is, the increase in the demand for skilled labour outpaced the increase in supply (Schmitt, 1995).

It is of some dispute in the literature as to what has actually caused this shift in demand (Gottschalk and Smeeding, 1997). The following now discusses the possible factors responsible for increasing the relative demand for skilled labour and, consequently, earnings dispersion. It is important to understand what may have influenced the trend in earnings dispersion, apart from changing returns to workers characteristics. This is because the analysis of later chapters attempts to determine which factors had the greatest impact upon dispersion, once changing returns to workers characteristics have been controlled for. The potential factors which are able to explain earnings dispersion within-groups fall into the categories of market forces and institutional changes. Considering market force explanations, these consist of demand and supply influences.

Demand based theories dominant in the literature are globalisation and skill-biased technological change. Globalisation explanations suggest that over the last two decades Western economies have become increasingly global. Between 1960 and 1990 the share of trade as a ratio to gross domestic product more than doubled in most advanced countries (Freeman, 1997). To the extent that the West's comparative advantage lies with skilled labour, globalisation might be expected to benefit those workers relative to the less skilled. Moreover, developed countries have become open to competition from lower wage developing economies, and firms have taken the opportunity to gain from these lower costs by substituting unskilled intensive production abroad. Skill-biased technological changes suggest that technological advances have favoured those workers with higher levels of skill. The possibility that such a relationship exists today has prompted the widely held conjecture that technology and skilled labour are relative complements, whilst technology and less-skilled labour are substitutes. Consequently, an increase in the rate of technological change, can be expected to raise the demand of the skilled relative to the less skilled.

Supply side explanations which have been popular in the literature are female participation and immigration (Topel, 1997). It is possible that both females and immigrants are substitutes for low-skill-endowed workers. If this is correct, a rise in the rate of female participation, or increased immigration will result in a decline in the earnings of the less skilled. Another possibility is that both females and immigrants are low skilled. Consequently, increasing female participation or immigration will result in an overall increase in the supply of less-skilled workers and so reduce wages.

The trade union movement has diminished, with just over half of all employees in the United Kingdom being employed in establishments where unions are recognised for pay negotiation (Corcoran and Wareing, 1994). To the extent that unions have maintained reasonable levels of pay for the less skilled in the past, a marked decline in collective bargaining can be expected to have influenced earnings dispersion.

Having briefly introduced the themes dominant in the literature, the following examines market force and institutional change explanations in greater depth.

2.3 The role played by market forces

Explanations associated with market forces are based upon demand and supply analysis. This section considers, firstly, demand explanations for increasing earnings dispersion and, secondly, supply theories. The former is based upon increased globalisation and skill-biased technological changes, where such changes have favoured those workers with higher skill endowments. Finally, supply side pressures include increased female participation and immigration, where these groups possibly act as substitutes to low-skilled males. It is also possible that either females or immigrants actually increase the supply of low-skilled labour, hence depressing its price and raising dispersion between the skilled and low skilled.

2.3.1 Globalisation

A common demand shock referred to in the literature is that of increased international trade which coincided with the increase in earnings inequality. Since the end of the 1960s, globalisation has occurred as a result of better communications and transportation (Freeman, 1997). The impact of international trade upon wage relativities is predominantly based upon the Heckscher-Ohlin model of trade, that is, factor price equalisation. The theorem states that under certain conditions free trade in final goods brings about international parity of factor prices, that is, in the case of labour wages. Assume that m goods are traded at world prices $\mathbf{p}$, and are produced through constant returns to scale technology - where technology is the same across borders, requiring m factors of production with input coefficients $\mathbf{A}$, giving an m×m matrix. Factor prices in country 1 are given as $\mathbf{w}_1$. Equilibrium implies that $\mathbf{p} \leq \mathbf{w}_1\mathbf{A}$ and, in the instance of positive production, that $\mathbf{p} = \mathbf{w}_1\mathbf{A}$. Under such a scenario, providing that the previous equation holds and **A** has full rank, then $\mathbf{w}_1 = \mathbf{p}\mathbf{A}^{-1}$. Factor prices are thus determined by the world prices of traded goods $\mathbf{p}$, and should be identical across countries. This type of framework implies that if one country has lower wages than another country, then, if factor prices do not converge, production tasks will shift to the country with lower wages. Consequently, factor price equalisation has led to the belief that low-skilled individuals are subject to intense downward pressure upon their wages through *Outsourcing*.

The position of the low skilled can be seen to have worsened in the event of outsourcing, where firms transfer those tasks formerly undertaken by low wage domestic workers in economies where the wages are much lower. Trade with lower wage countries, such as East-West trade, makes less-skilled labour in advanced countries (the West) and skilled labour in developing countries (the East) less scarce, and can thus be expected to reduce wages. The mechanism by which the relative earnings gap between the skilled and unskilled increases occurs in three stages. First, the distribution of tradable goods produced domestically shifts away from unskilled intensive production toward skill-intensive goods. Second, many previously low-skilled workers in this sector are forced into the non-tradable sector, such as service industries where wages are lower, which finally results in a fall in their relative wages (Freeman, 1995).

The problem of explaining earnings dispersion through globalisation, is that international trade only influences dispersion in the tradable sectors of the economy. Also, all explanations based on increases in trade are unable to explain the rising skill intensity in non-traded goods. That is, in spite of having to pay more for skilled labour, employers have chosen to hire more skilled workers (Gottschalk and Smeeding, 1997). This is contrary to the theoretical movements in skill intensities implied by the trade hypothesis.

2.3.2 Skill-biased technological changes

Another demand shock, which is consistent with increases in both the skill intensity and skill premium within narrowly defined groups, is widespread skill-biased technological change (Levy and Murnane, 1992). The impact of skill-biased technological change is dependent upon the ease of substitution of low-skilled labour for higher skilled workers. It is possible that the effect of technological change may have different impacts across industries. Johnson (1997) identifies different types of technological change. Given a production function of the form $Y = \psi(L_s, L_u, K)$ where Y is output, K is the capital stock (dependent upon technology), L_s is the input of skilled labour and L_u is the input of unskilled labour, the effects are shown in Table 2.1, below. The impact of both intensive and extensive skill-biased technological change would be to increase the demand for skilled labour and to raise the wages of higher skilled workers, leading to greater wage dispersion. In both cases, skilled labour and capital are complementary, so following technological change the demand for skilled workers increases, hence raising wages. The difference is that intensive technological change means that skilled workers become more productive in jobs they already do.

Table 2.1 Identification of the types of technological change

	Type of technological change	*Explanation of the impact upon wages*
1	Intensive	Skilled labour becomes more productive in jobs that they already perform, so the rate of change between capital and skilled labour is positive : $\frac{\partial K}{\partial L_s} \rangle 0$. This causes an increase in the demand for skilled labour, $\uparrow DL_s$, and for skilled wages to rise, $\uparrow W_s$
2	Extensive	Skilled workers become more efficient in jobs previously performed by the low skilled and, as a result, displace those with lower skill endowments : $\frac{\partial K}{\partial L_s} \rangle 0 \Rightarrow \uparrow DL_s \Rightarrow \uparrow W_s$
3	Neutral	Technological progress raises the efficiency of all groups of labour proportionally : $\frac{\partial K}{\partial L_s} \equiv \frac{\partial K}{\partial L_u}$. As a result, demand rises for both groups. $\uparrow DL_{s,u}$, and so the wages of both groups increase, $\uparrow W_{s,u}$
4	Assembly line	Labour shifts from skilled to unskilled, where simple repetitive tasks require raw labour. This means that the degree of complementarity between less-skilled labour and capital is greater than for high-skilled labour and capital, so $\frac{\partial K}{\partial L_u} \rangle \frac{\partial K}{\partial L_s}$. Consequently, demand for less-skilled workers increases, $\uparrow DL_u$, and wages rise, $\uparrow W_u$

Where $(\partial K \div \partial L_i)$ is the marginal rate of substitution.

The situation is different under extensive technological change, where skilled workers displace unskilled labour in jobs previously performed by the lower skilled. Neutral technological change would yield proportional demand changes for both groups of labour, where both the skilled and unskilled are complementary to capital, consequently increasing wages of both groups, but leaving the distribution of earnings unaffected. The impact of assembly line demand shifts is that demand rises faster for lower skilled labour than for high-skilled workers, where both skilled and unskilled labour are complementary to capital, thus raising the wage of the low skilled at a faster rate and narrowing earnings dispersion.

2.3.3 Substitution possibilities - Female participation and immigration

The effects of supply shifts upon wage dispersion are also an important factor to consider. It is possible that certain supply changes may have exacerbated the trend of rising dispersion, arising from skill-biased technological change or globalisation, notably immigration and female participation (Topel, 1994, 1997).

The theoretical impact of immigration upon the earnings dispersion is dependent upon the type of modelling framework employed. Most important, however, is the degree of substitutability between immigrants and workers in the economy who are facing pressure from lower wages. In a closed economy immigrants will tend to lower the price of factors for which they are perfect substitutes and have an ambiguous effect on the price of factors for which they are imperfect substitutes. Those factors to which immigrants are complements can expect to witness an increase in price following an increase in the supply of immigrants. Consider a closed economy where capital and skilled labour are complementary and unskilled labour is a substitute for capital and skilled labour. If the majority of immigrants are unskilled then the wage of unskilled workers will fall, whilst the return to capital and skilled labour is ambiguous. The fall in the premium of unskilled labour will enduce producers to substitute away from capital and skill-intensive production to the cheaper more abundant unskilled labour. If the majority of immigrants are skilled then the opposite is the case : the skilled wage is lowered, which results in a rise in the demand for its complementary factor capital.

In an open economy the results of immigration are somewhat different. If technology is assumed to be the same across countries, trade will be driven by factor endowments. Factor price equalisation will arise if factor endowments between countries are not too dissimilar. Immigration will cause production of the more labour intensive goods to increase, leaving factor prices unchanged. The adjustment mechanism in an open economy is not through factor prices, as in a closed economy, but rather through labour embodied in traded goods. Immigration will cause the country to compensate by exporting more labour as embodied in goods. However, such a modelling framework means that if factor price equalisation holds, there is no reason for migration to occur between countries. One possible explanation for labour to move from poor to rich countries is that rich countries have tariffs on goods that make use of unskilled labour, in an attempt to raise wages above the world price. If labour is mobile, immigration of the unskilled will continue until the wage rate of such labour returns to the world level, where the country will specialise in the production of the good that makes intensive use of unskilled labour. Once the economy becomes specialised, the impact of immigration will have effects similar to those of the closed economy case. In reality, immigration is restricted and, as such, it is possible that the wage could remain above the world price level for some time.

The impact of supply changes to the labour market could result in higher earnings inequality, particularly if females are less skilled than males, as in the above scenario of a closed economy. An increase in the supply of females would depress the wage rate of unskilled labour.

It is feasible that the rising supply of female workers, or immigrants, can affect the wages of males through substitution possibilities, where increased supply results in a decline in demand for low-skilled males. This can be shown by using a conventional CES production function, including female/immigrant labour input in the production function, where N_s and N_u refer to male skilled and unskilled labour respectively (Hamermesh, 1993):

$$Y^{\rho} = \left[\left(\sum \alpha_s N_s^{\rho}\right) + \left(\sum \alpha_u N_u^{\rho}\right) + \left(\sum \alpha_z N_z^{\rho}\right)\right]^{1/\rho} \equiv Y^{\rho} = \phi \sum_i \alpha_i N_i^{\rho}$$

$\rho \leq 1, \sum \alpha_i = 1$ where $1-\rho = 1/\sigma$, α_i is a productivity coefficient and σ is defined as the elasticity of substitution. The input, given as z, represents either female participation and/or immigration. The degree of substitutability of this group to low-skill endowed males is given as $\sigma_{u,z} = \frac{\partial W}{\partial L_u \partial L_z} \rangle 0$. Under the assumption that either females or immigrants act as substitutes to males of low skill endowment, the impact is to depress the wages of the unskilled.

2.4 The role of institutional changes in the labour market

The problem with market force explanations for rising earnings dispersion is that, because most other labour markets in the industrialised world have been exposed to similar technological and trade shocks, it would be expected that they have also experienced widening earnings dispersion. Yet, the only country to experience rapidly rising wage inequality apart from the United Kingdom has been the United States (Katz, Loveman and Blanchflower, 1995). A possible explanation for this occurrence is the differing array of institutional arrangements across countries, where labour market institutions can mitigate the impact of supply and demand changes on the structure of wages. For instance, both the

United States and the United Kingdom have a relatively decentralised bargaining process, in comparison with other countries such as Germany (Calmfors and Driffill, 1988). As a consequence, demand and supply shocks have a more direct impact upon wages and employment in the United States and the United Kingdom, where union power to oppose market driven forces has been considerably weakened in recent years. The following focuses upon the declining role of collective bargaining, as union membership and density has fallen in the United Kingdom. This has led to demand and supply shocks having an immediate and powerful impact upon earnings (Schmitt, 1995). In addition to the variations between countries, differing institutional arrangements between industries in the United Kingdom may also go some way in explaining industry specific experiences of wage dispersion. For instance, union density varies significantly between industries, from 4 per cent in computing to 88 per cent in electricity generation and supply (Corcoran and Wareing, 1994).

Unions have the tendency to compress the wage structure, as one of the aims of trade unions may be to produce a fair allocation of earnings amongst its members. So, it can be argued that a reversal of the fall in collective bargaining arrangements would reduce wage disparities. However, the equalising impact of unions on the wage structure is not as clear cut as one might think. Whilst those covered by union bargaining experience a decrease in the level of wage inequality, the overall wage distribution may actually widen, as the disparity between covered and uncovered workers actually increases. The net impact of unions on earnings distributions is therefore ambiguous (Freeman, 1993).

2.5 Alternative explanations of earnings dispersion

There are particular problems with the conventional analysis of the labour market based upon the demand and supply framework. In particular, the analysis implies that there should be a trade off between wage dispersion and unemployment. However, there is no clear evidence to substantiate this. Moreover, the incidence of unemployment has not just fallen upon the unskilled but also has risen for skilled labour (Nickell and Bell, 1996). These two empirical occurrences are anomalies that are difficult to explain by the demand and supply framework. Although the methods adopted in later chapters test the conventional demand and supply framework, it is important to have an understanding of alternative explanations.

In the conventional labour market framework, shifts in the demand for labour towards higher skill endowed workers is given a major role to play in explaining the widening gap in earnings. These demand shifts can be caused by technological change, globalisation, institutional change, or supply side impacts from females or immigrants (as argued in the previous sections). Recently, it has been advanced that organisational change can help to explain rising earnings dispersion by requiring workers to be able to shift between numerous tasks (Lindbeck and Snower, 1996). The organisational change hypothesis is multi-faceted and can encapsulate each of the previously introduced concepts which could potentially explain earnings dispersion. The change is propelled through advances in computing, information technology and telecommunications technologies in conjunction with human skills. A major implication is that the transformation is requiring new forms of organisation activity which may be exerting a major influence upon earnings dispersion (Snower, 1998). Snower (1998) is uneasy to assess organisational change as another potential factor – alongside technological change or globalisation for instance – that influences the demand for skilled labour. Moreover, organisational change is actually redefining skills, increasing the demand for a new set of labour market characteristics requiring versatility across tasks, the ability to learn new tasks, the ability to operate in a team environment and so on.

The organisational change approach gives scope for explaining earnings dispersion beyond the competitive labour market approach. Earnings dispersion can be determined by factors that cannot be captured within the conventional labour market analysis based under perfect competition and perfect information – in particular efficiency wages and the insider-outsider frameworks. Efficiency Wages (see for instance, Stiglitz, 1985; and Weiss, 1980) can occur when managers have imperfect information about their employees actual productivities and find it worthwhile to offer wages to stimulate performance. When the firm increases its wages it stimulates productivity and reduces turnover costs. The firms incentive is to minimise efficiency wages which means the wage offered may be above the market equilibrium price and so results in unemployment. Insider-Outsider models (see for instance, Lindbeck and Snower, 1986, 1987) can arise on account of labour costs it is often expensive for firms to replace their established incumbent (insiders) workers by new recruits (outsiders). Knowing this the insiders raise their wage above the market clearing level without running the risk of dismissal and so unemployment occurs. Both types of model offer a different account of earnings dispersion that differs substantially from the conventional demand and supply framework. In the conventional model dispersion arises from differences in the productivity of individuals. However, in the efficiency wage and insider-outsider models it also reflects imperfect information and labour turnover costs and so earnings dispersion may exceed productivity dispersion. Assuming that within holistic organisations higher skills are associated with more diverse jobs requesting mulit-tasking then insiders are likely to be more difficult to replace than outsiders. Then, aside from productivity differences the insiders have an incentive to push for higher wages than the unskilled. Organisational reforms can thus generate earnings dispersion not only by creating new productivity differentials, but also by turning wages into a more powerful instrument for stimulating productivity and creating new turnover costs.

This section has introduced alternative explanations capable of explaining rising earnings dispersion based around imperfect markets. Whilst these influences are of significance, the remainder of the study focuses explicitly upon explanations based around the competitive labour market framework. There are essentially two reasons for this: firstly, the majority of the current research upon earnings dispersion is based around the demand and supply model – in the 1997 review of earnings dispersion in the Journal of Economic Literature (Gottschalk and Smeeding, 1997) there was no reference to alternative explanations; secondly, there is inadequate data (both individual and firm level) to carry out an empirical investigation over time – which is a key motivation for this study. Consequently, the remainder will focus exclusively upon the demand and supply explanations introduced in sections 2.3 and the role of institutional change section 2.4.

2.6 Modelling the impact of market forces and institutional change

Having discussed the possible causes of increasing earnings dispersion and decomposed the causes into demand, supply and institutional change, the following section outlines a theoretical model (based around a closed economy) of the labour market. The framework is adopted to show the impact of demand, supply and institutional change upon wage dispersion, which motivates the empirical analysis set out in Chapter Four, and the results in Chapter Seven.

Consider an economy with *i* types of labour. The economy's output (Y) is produced by a CES production function that is homogeneous of degree one :

$$Y^{\rho} = \phi \sum_{i} \alpha_i N_i^{\rho}$$

$\rho \leq 1$, $\sum \alpha_i = 1$ where $1-\rho = 1/\sigma$, and σ is defined as the elasticity of substitution. The *i*th type of labour is given by N_i and the α_i parameters reflect productivity. Given competition in the product market, the demand for labour in terms of its price is given as :

$$W_i = \alpha_i \phi (N_i / Y)^{-1/\sigma} = \alpha_i [(1-\upsilon_i) L_i / L]^{-1/\sigma} X \qquad \textbf{(2.1)}$$

where W_i is the real wage, L_i is the labour force in the *i*th sector, L is the total labour force, υ_i is the unemployment rate amongst type *i* workers and X is an aggregate productivity factor, $X = \phi (Y / L)^{1/\sigma}$. Wages in each sector are determined by the wage function, which may contain elements of labour supply, efficiency wages or union bargaining (Blanchflower and Oswald, 1994). Such a wage function takes the form :

$$W_i = \gamma_i g(\upsilon_i) X \qquad g' < 0 \qquad \textbf{(2.2)}$$

The coefficient γ_i is an indicator of wage pressure in the sector. The short run level of unemployment for each group is given by eliminating W, such that :

$$\upsilon_i = 1 - (1 - \upsilon_i) = f(\gamma_i / \alpha_i, L_i / L) \qquad f_1 > 0, f_2 > 0$$

Thus, wage pressure γ, relative to productivity α, and the relative size of each group can cause increases in unemployment. Similarly, wages are determined as follows, where :

$$W_i = \omega(\gamma_i, \alpha_i, L_i / L, X) \qquad \omega_1 > 0, \omega_2 > 0, \omega_3 < 0, \omega_4 > 0$$

Wages are increasing in productivity, wage pressure and aggregate productivity, and decreasing in the relative size of each group.

Restricting the model to three groups of labour : skilled (s), unskilled (u), and other labour inputs (z) i=s,u,z, we get, from equations 2.1 and 2.2 :

$$W_s = \omega_s(\gamma_s, \alpha_s, L_s / L, X),\ W_u = \omega_u(\gamma_u, \alpha_u, L_u / L, X), W_z = \omega_z(\gamma_z, \alpha_z, L_z / L, X)$$

where $\omega_{i1}>0$, $\omega_{i2}>0$, $\omega_{i3}<0$, $\omega_{i4}>0$. From the first two equations, wage dispersion between the skilled and unskilled, ignoring z, can be given as :

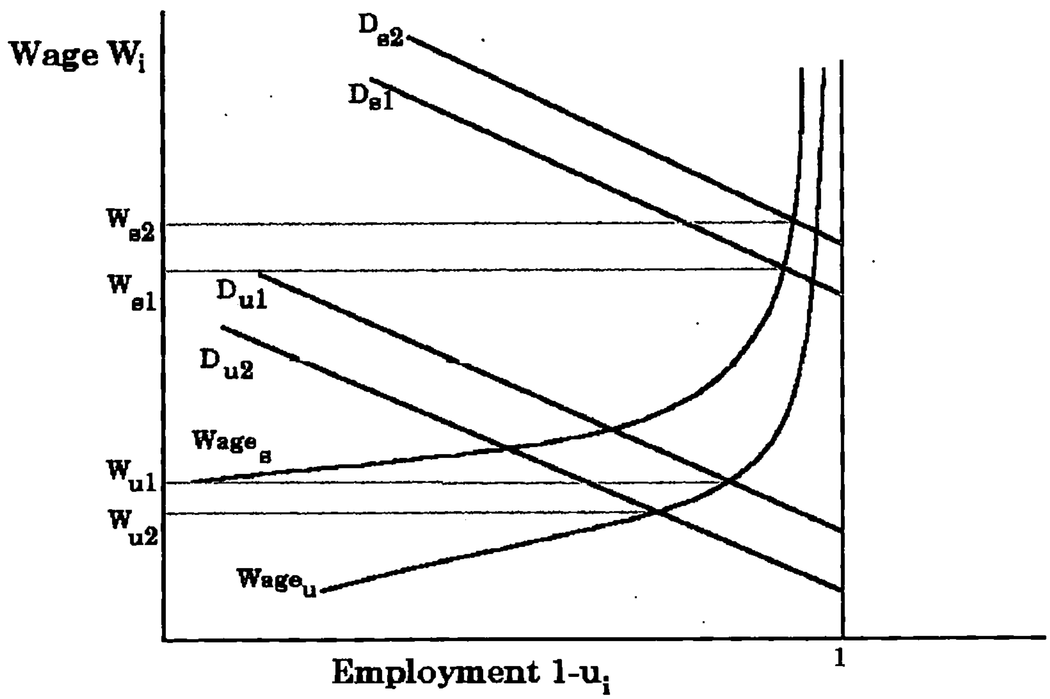
$$\left.\left(\frac{W_s}{W_u}\right)\right|_z = \lambda\left[\frac{\gamma_s}{\gamma_u}, \frac{\alpha_s}{\alpha_u}, \frac{L_s}{L_u}\right] \qquad \lambda_1>0,\ \lambda_2>0,\ \lambda_3<0 \qquad \textbf{(2.3)}$$

The expression in equation 2.3 shows the relative wage of the skilled to unskilled to be influenced by relative wage pressure, relative productivties and the relative size of each group. Market forces operate through $\frac{\alpha_s}{\alpha_u}$ and $\frac{L_s}{L_u}$, where earnings dispersion is increasing in the former and decreasing in the later. Institutional changes influence earnings dispersion through $\frac{\gamma_s}{\gamma_u}$. Given the expression in equation 2.3, we can now examine the impact of demand, supply (collectively market forces) and institutional change upon wage dispersion.

2.6.1 The role of market forces

The short run equilibrium is shown in Figure 2.2, below, where the two groups analysed are the skilled (s) and the unskilled (u), thus i=s,u. The vertical axis shows the wage rate for the two groups, and the horizontal axis gives employment for the two groups (s,u), $1-u_i$. Initially, labour demand for the two groups is given as Du1 and Ds1 respectively (from equation 2.1), forming an equilibrium where the curve intersects the wage curve Ws and Wu (from equation 2.2), and giving initial wages as Wu1 and Ws1. Consider the impact of a rise in the relative demand for skilled labour, as a result of either skill-biased technological change or globalisation.

Figure 2.2 The effect of market forces on the wages of the skilled and unskilled



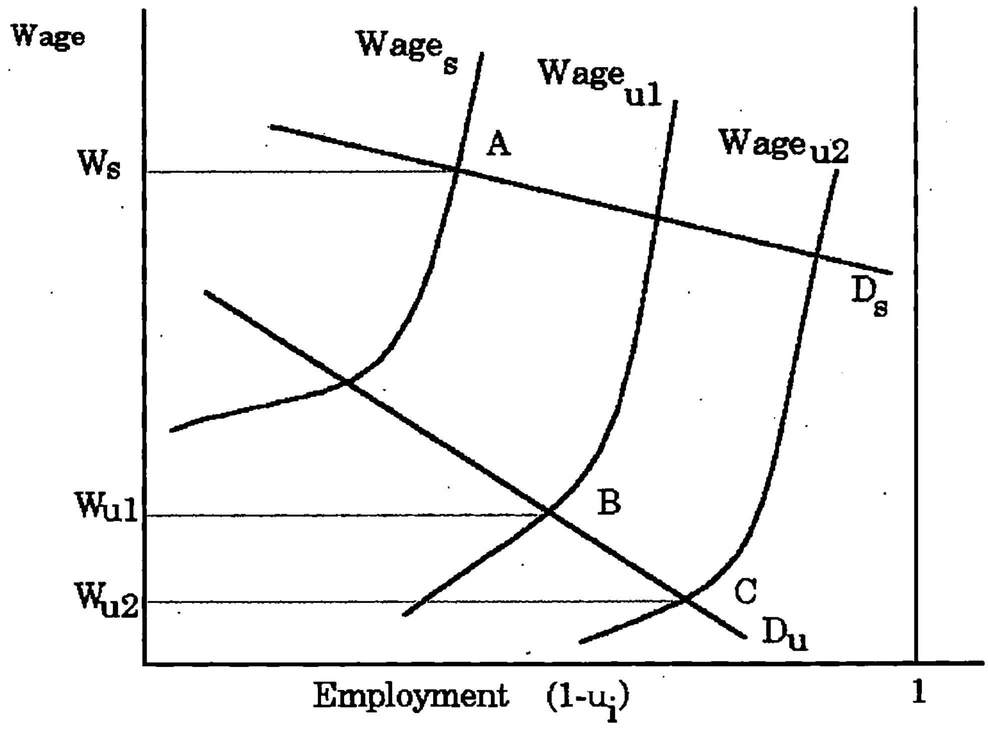
This can be modelled as a rise in α_s and a fall in α_u. Because $\lambda_2>0$, the relative wage W_s/W_u increases and so dispersion rises, since $\left(\frac{\partial W_s}{\partial \alpha_s} > \frac{\partial W_u}{\partial \alpha_u}\right)$. Diagrammatically, the demand for skilled labour will rise and their unemployment will fall as the demand curve shifts from Ds1 to Ds2, increasing wages from Ws1 to Ws2 (Ws2>Ws1). Further, because of the substitutability between capital and unskilled labour, the demand curve falls for the unskilled from Du1 to Du2, and consequently their wages fall from Wu1 to Wu2, (Wu2<Wu1) and unemployment rises. Wage inequality between the two groups has also increased, since [Ws2-Wu2]>[Ws1-Ws2], i.e. $\left(\frac{\partial W_s}{\partial \alpha_s} > \frac{\partial W_u}{\partial \alpha_u}\right)$. In the longer term the unskilled may respond by investing in additional human capital, through training in order to become more skilled, and as a result both relative wages and employment will tend to move back towards their initial position as L_s/L_u increases, and so W_s/W_u falls (Nickell and Bell, 1995).

From the supply side, two of the common most groups which are considered to have had an impact upon wage dispersion are increasing female participation and immigration, given as the other labour inputs (z). If both groups are considered to be substitutes for the unskilled, then the situation is as described above, where demand for the unskilled falls. This is because $\left(\frac{\partial L_s}{\partial L_z}\right)>0$ and increases in L_z result in an increase in α_s, and so dispersion rises. This is analogous to the case given above in Figure 2.2. An alternative is that the entrance of females or immigrants into the labour market results in an increase in the supply of unskilled labour. Consider the case where the unskilled labour group consists of unskilled males (um) and other labour inputs (z). That is, $L_u = L_{um} + L_z$, and as L_z increases so does L_u, resulting in a fall in L_s/L_u. As a result from equation 2.3, it can be seen that because $\lambda_3<0$ that a fall in L_s/L_u results in a rise in dispersion.

2.6.2 The role of institutional change

The declining power of trade unions in particular can also result in increasing wage dispersion in the short run. If the wage pressure coefficient γ_u falls relative to γ_s, then the wage pressure of the skilled relative to the unskilled rises. From equation 2.3 above, because $\lambda_1>0$ and γ_s/γ_u rises, wage dispersion will also increase. The effect works through equation 2.2 where the wage function for the unskilled contracts relative to the skilled. Again, using the demand and supply diagram based upon the above set of equations, Figure 2.3 shows that the labour market is initially in equilibrium at points A and B. The initial equilibrium yields a wage Ws and Wu1 for the skilled and unskilled respectively, from where the appropriate demand curve intersects the relevant wage curve. As the wage pressure of the unskilled falls, due to declining trade union power, the wage function for the unskilled expands along the demand curve (as militancy falls, allowing unemployment to decline for the unskilled). As a result, the wage of the unskilled falls from Wu1 to Wu2, and so wage dispersion between the skilled and unskilled increases, since [Ws-Wu2]>[Ws-Wu1]. From equation 2.3 the outcome is obvious, because as γ_u falls relative to γ_s, given $\lambda_1>0$, the expression γ_s/γ_u rises, and so W_s/W_u increases.

Figure 2.3 The impact of institutional change upon the labour market



2.7 Conclusion

The major theories capable of explaining earnings dispersion have been identified as stemming from market force explanations and institutional changes. More specifically, the key factors which are able to influence earnings dispersion occurring within narrowly defined groups are: skill-biased technological change (Johnson, 1997), globalisation (Wood, 1994), female participation (Topel, 1994, 1997), immigration (Topel, 1994, 1997) and declining collective bargaining (Freeman, 1993). The purpose of this study is to provide an empirical framework within which the competing theories can be tested and compared to the theoretical model.

Having introduced the main themes in the literature capable of causing earnings dispersion within narrowly defined groups, such as education and experience, and introduced the theoretical model, the following chapter discusses the empirical support for the competing theories. From this, Chapter Four develops an empirical approach to test the competing theories, stemming from techniques grounded in the empirical literature of Chapter Three.

3

An Assessment of Empirical Research on Earnings Dispersion

3.1 Introduction

A number of approaches have been adopted to test the competing causes and influences upon earnings dispersion identified in Chapter Two. Two of the most common types of underlying theoretical frameworks used are human capital models and production/cost functions. Human capital models have applied data based upon individuals to control for the possibility of differing distributions of worker characteristics across populations. These models have also commonly included either a technological change indicator, female participation, immigration, or an indicator of unionisation. Human capital models are based upon price outcomes, that is, wages. An alternative approach to human capital models has been to use production functions and assess quantity outcomes. Typically, establishment level data has been used to assess the impact of the competing theories when employing production functions. Problems associated with both methodologies can be identified as unobservable factors - which are potentially correlated with regressors and endogeneity bias. Sections 3.2 and 3.3 consider the previous research in detail, discussing how the competing theories identified in the previous chapter have been tested, the impact upon earnings dispersion, and problems associated with the techniques used.

3.2 Market Forces

3.2.1 Empirical evidence of globalisation

Empirical testing of the impact of international trade upon wages has relied upon a number of approaches including factor content analysis, price analysis and factor decompositions.

Factor content analysis uses data on the *factor content* of import and export industries and considers the resultant impact upon factor endowments. Underlying the factor content theory is the notion of factor price equalisation, based upon the Heckscher-Ohlin model of trade. Such an approach estimates the effect of globalisation on the demand for labour at given wages levels, that is, the domestic and foreign inputs used to produce goods. Given estimates of the labour skills used in various sectors of the economy, it is possible to estimate how changing imports and exports affect the demand for high- and low-skilled workers (at given relative wages and prices). Empirical testing using the factor content analysis in the United States has decomposed within-industry and between-industry shifts in relative demand for particular industrial sectors, given as imports, exports and defence procurments (Berman, Bound and Griliches, 1994). Focusing upon the sectors - imports, exports and defence procurements, over the period 1979 to 1987, Berman et al (1994) analyse the impact of trade. Using data from the NBER *Trade Immigration Labour Market* database, the analysis implies that the influence of trade is small. They argue that the change in both industry-sector shares and the proportion of skilled labour is due to skill upgrading, which is unrelated to either trade or defence sectors. As a result, Berman et al (1994) reject the possibility of outsourcing as an explanation of rising earnings dispersion. They note that the 1987 *Census of Manufacturers* reports that only 8 per cent of all materials purchased in manufacturing can be attributed to foreign trade. Based upon this figure, Berman et al (1994) estimate that replacing all outsourcing with domestic activity would only raise employment in the manufacturing sector by 2.8 per cent for production workers.

This type of empirical approach has been criticised because the conventional estimates are incorrect in that the calculations fail to recognise that trade is non-competing (Wood, 1994). Thus, the size of trade effects is understated. The factor content methodology involves calculating the amounts of skill, labour and capital embodied in trade flows. Such a theory assumes that the number of skilled and unskilled workers displaced by a pound's worth of imports in each sector is equal to the amount of exports produced by a pound. This rests upon an implicit assumption that the imports in each statistical category are goods of the same type and level of skill intensity as those goods produced in the corresponding domestic sector. It has been argued that this assumption is unrealistic as imports of manufactured products from developing economies are of low-skill intensity and are no longer produced in developed countries on a significant scale (Wood, 1994, 1995). This is particularly true of intermediate products, such as electronics, where assembly line electrical goods have been produced in low-wage countries. Thus, developed nations have moved towards skill-intensive manufacturing, whilst imports from developing countries are of low skill intensity and so are non-competing with domestic production. Conventional measures of factor content understate the number of unskilled workers required to meet the demand for goods currently imported, in the absence of trade. By measuring the amount of labour used to produce such imports, adjusting for the higher wages of developed countries and the fact that to produce such goods would cost much more domestically, the estimates of Berman et al (1994) are found to be too small (Wood, 1994, 1995). The corresponding percentage change in demand for labour in manufacturing caused by trade shows that demand fell for the unskilled relative to the skilled by 21.8 per cent.

Another implication of the factor content approach is that the methodology adopted may lead to an underestimate of the extent of outsourcing. Firstly, an imported intermediate input may be processed and resold several times between different firms, but is only counted as an import when first entering the economy. As a result, there may be double counting of domestic materials in comparison to imports, and so the 8 per cent estimate found by Berman et al (1994) may be an underestimate. Secondly, the Census excludes all offshore assembly and contracting, and so such factors are not included in the measure of outsourcing. An example of this is the company Nike, which employs 2,500 people in the United States for marketing and other headquarter services, whilst 75,000 persons are employed in Asia producing shoes which are sold to Nike (Feenstra and Hanson, 1996). Nike shoes are not counted as materials, but as finished products, and so do not appear in the Census measure of outsourcing.

In an attempt to overcome the above potential problems, a more general definition of outsourcing can be employed (Feenstra and Hanson, 1996). In addition to imports by US multinationals, this revised measure also includes all imported intermediate or final goods that are used in production of, or sold under the brandname, of an American firm. Using firm level data from the *NBER Trade Immigration Labour Market* database of 450 four digit manufacturing industries, Feenstra and Hanson (1996) estimate the impact of trade. The results indicate that 15 to 33 per cent of the shift towards non-production labour within manufacturing industries, over the period 1979 to 1985, is explained by the rising import share.

Factor content studies have also been criticised on the ground that observed trade patterns do not necessarily reflect the impact of price pressures operating through trade. Rather than estimating the impact of trade from the quantity side, as above, it has been suggested that prices should be analysed to study how trade has affected the demand for low-skilled workers. In the United States, the impact of international trade based upon prices has been examined by Lawrence and Slaughter (1993), using data from the *Bureau of Labour Statistics* and the NBER *Trade Immigration Labour Market* database. They correlate changes in import prices with the share of production workers across industries and find that, once prices are adjusted for changes in total factor productivity, the prices of less-skill-intensive goods fell, but only slightly. Larger estimates have been found in the United States (Leamer, 1996) where, estimating the effects of trade upon factor prices, trade can account for 40 per cent of the decline in wages of the less skilled.

A further possible way of analysing the impact of trade based upon price rather than quantity analysis is to use time series techniques to examine wage dispersion. Moreover, Borjas and Ramey (1994) use cointegration techniques to investigate the co-movement of wage dispersion to underlying causes, such as technological change, declining unionisation, female participation, immigration and globalisation. The cointegration approach considers whether wage dispersion follows the same trend[1] as its potential causes. A particular advantage of cointegration analysis is that it can be used to assess what has influenced dispersion over time. Over a period of time it is likely that wage dispersion, technological change, unionisation, female participation, immigration and globalisation have been subject to stochastic trends. A major problem for empirical analysis is that trended data can give rise

[1] Non stationary data contains stochastic or random trends, while stationary data series contain deterministic i.e. fixed trends.

to spurious regressions (Chapter Four, section 4.4). One possible remedy is to difference a series until it becomes stationary; however, this is not an ideal solution. Cointegration analysis can be used, to consider whether a linear relationship exists between two or more non-stationary variables, where deviations from this relationship are stationary. Adopting such an approach for the United States, employing data from the *Current Population Survey* over the period 1963 to 1988, it has been found that the imports of durable goods account for most of the change in wage differentials (Borjas and Ramey, 1994).

A weakness of the work by Borjas and Ramey (1994) is that the approach they adopt considers each possible explanation of earnings dispersion one at a time, not all at once. In other words, the framework they adopt is bi-variate. A more robust approach is given by using multi-variate cointegration techniques to examine the stochastic trends in several variables over time (Johansen, 1988; Buckberg and Thomas, 1996). Using the same data as Borjas and Ramey (1994), Buckberg and Thomas (1996) find that trade effects dominate technological change, although both are significant in explaining rising dispersion from 1970 to 1990. Having discussed the factor content approach based upon both quantity and price data, the following considers empirical evidence of the impact of globalisation based on factor decompositions.

Haskel and Slaughter (1999) argue in favour of the trade hypothesis on the basis that it is the sector bias of technological change which is of significance. To demonstrate the importance of sector bias what is important for wages is the potential flow of workers between sectors. It is these flows between sectors which can cause wage adjustments. Total Factor Productivity changes in the 1980s were not concentrated in the skill intensive sectors – rather there was a uniform impact across sectors. Hence Haskel and Slaughter (1999) conclude that changes in technological progress could not have caused wage inequality since they would have been concentrated in the skill intensive sectors.

Recently, Wood (1998) has also argued in favour of the trade hypothesis. He suggests that whilst the shift in demand towards higher skilled labour was as a result of skill biased technological change, the acceleration of the relative demand shift – particularly during the 1980s – was as a result of globalisation. If this is the case then both technology and trade would seem to be actually interacting with each other, although technology caused the demand shift the sharp rise in earnings dispersion was triggered by trade.

An argument in favour of trade effects is that the Heckscher-Ohlin model of trade, with small open economies and two factors of production - skilled and unskilled labour - is that it is not consistent with the skill-biased technological change argument outlined in Chapter Two, section 2.3.2. This is because under the Heckscher-Ohlin assumptions skill-biased technological change is unable to change the wage structure unless the shock is sector biased. It is on such grounds that the skill-biased technological change hypothesis, in explaining the decline in demand for the low skilled, has been rejected (Leamer, 1996). This has significant implications as the long run Heckscher-Ohlin model is widely considered to be the relevant model for analysing the impact upon wages of increased trade in manufacturing between developed economies and less developed economies. However, it has been pointed out that *pervasive* skill-biased technological change can affect relative wages, since an integrated world will respond to such shocks as a closed economy (Krugman, 1995). The pervasive skill-biased technological change argument has testable implications. Firstly, the percentage of within-industry changes dominates the percentage of between-industry effects (Berman, Bound and Griliches, 1994). That is, the variation in employment shares is down to changes in the reallocation of labour within particular industries. Secondly, and of greater importance, these shifts have been concentrated in the same industries across different countries (Berman, Bound and Machin, 1997). Thus, the pervasive skill-biased technological change argument implies that within-industry changes should be correlated across countries producing the same good. Indeed, in the OECD, over the period 1980 to 1990, the shift towards the usage of higher skilled labour has occurred within the same industries across countries (Berman, Bound and Machin, 1997). So, whilst local technological change does not influence wages under the Heckscher-Ohlin framework, evidence of pervasiveness deals with a major criticism of skill-biased technological change as a cause of inequality.

If trade is the main demand factor, rather than skill-biased technological change, then the demand for high-skilled labour would not have risen. Instead, due to the relative reduction in the price of low-skilled labour, firms would substitute towards this group. That is, within-industry employment shifts in developed countries should be in favour of less-skilled workers. However, the factor ratios of skilled to unskilled labour have shifted in favour of the more skill endowed in the economy. So, whilst a trade based explanation predicts substitution towards lower skilled labour, the substitution actually witnessed over the 1980s has been towards higher skilled workers. Indeed, recent evidence based upon OECD countries has found that, even within very disaggregated non-traded sectors, there have been increases in skilled employment (Desjonqueres, Machin and Van Reenen, 1998). The following discusses the empirical literature of skill-biased technological change, which not only predicts the correct direction of skill substitution, but is also consistent with trade theory if of a pervasive nature - which empirical evidence suggests (Berman, Bound and Machin, 1997).

3.2.2 Empirical evidence of skill-biased technological change

One of the major theoretical arguments for rising wage dispersion is that technological change has favoured the skilled worker. The evidence that skill-biased technological change has increased demand in favour of skilled labour is twofold, both indirect and direct. Indirect evidence has relied upon factor decompositions and residual earnings dispersion, whilst direct evidence is based upon using indicators of technological progress.

Factor decomposition has typically decomposed ratios of one skilled group to a lower skilled group into between-industry and within-industry components (Berman, Bound and Griliches, 1994). For instance, the aggregate share of skilled workers relative to lower skilled workers can be decomposed into between and within components as follows :

$$\Delta Sn = \sum_j \Delta S_j \overline{Sn_j} + \sum_j \Delta Sn_j \overline{S}_j \qquad \textbf{(3.1)}$$

Where there are $j=1...J$ industries in manufacturing, S_j is the employment share of the jth industry in total economy employment, Sn_j is the share of skilled workers in employment in the jth industry, and a bar denotes a mean value. The first term measures the between-industry effect, that is any reallocation of employment from low-skill- to high-skill-intensive industries. The second term represents within-industry effects, that is, an increased use of high-skill endowed labour within industries. Empirical evidence based upon the above decomposition was first available from the United States (Berman, Bound and Griliches, 1994), based upon 450 manufacturing firms from the *Annual Survey of Manufacturers* (ASM). Over the period 1979 to 1987, the employment share of non-manual labour rose by 0.552 percentage points per year. Of this increase, 70 per cent of the aggregate rise took place within four digit industries. Similar results have been obtained in the United Kingdom

(Machin, 1996[b]), using establishment level data from the *Workplace Industrial Relations Survey* (WIRS). The non-manual employment share in the manufacturing sector rose by 0.367 per cent per annum over the period 1979 to 1990. Of that increase, 82 per cent occurred within three digit industries. Such an approach gives indirect evidence in favour of the technological impact hypothesis, where technology has favoured skilled workers. The following discusses more direct evidence of skill-biased technological change and the inherent problems involved with testing its significance.

3.2.2.1 Skill biased technological change : Human capital models

Whilst the above evidence came from firm level or establishment level data (ASM and WIRS), indirect evidence of relative demand shifts is also available from cross sectional data based upon the individual. It is possible to control for an individual's observable skills from a wage regression, as follows :

$$\omega_i = X_i\delta + \varepsilon_i \tag{3.2}$$

where ω_i is the log wage rate. Variables in X_i include education, experience, sex, race, industry indicators, regional indicators and so on. The vector δ is the return to such individual characteristics. By treating the residual, ε_i, from the regression as the value of unobservable skills, a measure of wage dispersion can be derived which is free from personal and human capital effects. Such an approach can be adopted to consider the importance of the unexplained or residual wage inequality, which represents within-group changes, by using simple equations where the log earnings are treated as a function of age and years of education (Machin, 1996[a]). Using individual level data from the *Family Expenditure Survey* (FES) for the years 1979, 1982, 1986, 1990 and 1993, Machin considers trends in both between-group inequality (the standard deviation of estimated wages) and within-group inequality (the standard deviation of the residual). From 1979 to 1993, within-group inequality increased by 23 per cent in the United Kingdom and dominated between group inequality. Skill-biased technological change represents one explanation for this rise in earnings dispersion amongst relatively homogeneous groups of individuals, that is, within education and experience groups.

The indirect evidence of skill-biased technological change, based both upon factor decompositions and wage residuals is open to criticism. Firstly, shifts occurring within particular industries towards more skilled labour and increasing returns to skilled labour relative to the unskilled only suggest that skill-biased technological change may have been the causal factor. Secondly, and a related argument, changes in technology - which are embodied in the aggregate production function - have not been directly observable or measurable. As a consequence, empirically this means that technical change is typically defined to be the amount of change in relative wages that cannot be explained by observable characteristics, that is the residual, ε_i. Over the past decades advanced nations have experienced rising average skill levels, as successive cohorts of workers enter the labour market with greater levels of educational attainment[2]. Without technical change it should be expected that the returns to educated workers would have declined, yet the opposite is true[3]. Thus it is hard not to infer that shifts in the relative demand for skilled workers, generated possibly by technical change, have outpaced rising supply, so that high skill wage premiums have increased.

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[2] Evidence for Great Britain, based upon the *General Household Survey*, shows that for the period 1974 to 1976 males with no qualifications constituted over half of the labour force (Schmitt, 1995). By 1986 to 1988 this group was less than one third of the total. Similarly, at the other end of the skill distribution, those males with a degree rose from just under 5 per cent to nearly 11 per cent over the same period of time (Schmitt, 1995).

[3] Between 1979 and 1993 in the United Kingdom Machin (1996[a]) found, using the *Family Expenditure Survey*, that the return to years of schooling rose from 0.06 to 0.067 log points.

Recently, to attempt to overcome some of the criticisms of skill-biased technological change, more robust evidence has been provided giving direct evidence of a significant correlation between wages and indicators of technological change. Consider the above earnings equation 3.2, augmented to include an indicator of an individual's computer use at work C_i, thus :

$$\omega_i = X_i\delta + C_i\gamma + \varepsilon_i \qquad \textbf{(3.3)}$$

If those individuals who use a computer receive higher wages, then this is direct evidence of the impact of technological change. An often cited example of this methodological approach is for the United States (Krueger, 1993), using individual level data from the *Current Population Survey* for the years 1984 and 1989. Krueger (1993) found that by including a binary indicator for computer usage in a standard wage equation, as above in equation 3.3, those individuals who use computers at work earn more. More specifically, such individuals earn 15 per cent to 17.6 per cent higher than their counterparts who do not use computers for the two years.

There are serious problems associated with using computer indicators in earnings functions. The large differentials associated with on-the-job computer use may just reflect that higher wage workers are more likely to use a computer at their place of work, implying that the indicator is endogenous. Hence, causality does not run from computers to earnings, but rather from earnings to computers. Hence, if workers who use new technology are better paid, is it because they are more able, or is it due to the fact that new technology increases their productivity? Indeed, evidence does suggest that the former is true (Doms, Dunne and Troske, 1997).

Table 3.1 The effect of different tools on pay

	1979	*1985 to 1986*	*1991 to 1992*
Pen/Pencil	0.055	0.055	0.050
Computer	0.025	0.076	0.083

DiNardo and Pischke (1997), Table 3, page 298. The coefficients show the impact upon log hourly wages. Based upon equation 3.3

Using cross sectional data from the *Qualification and Career Survey* conducted in 1979, 1985 to 1986 and 1991 to 1992, the impact of technology on wages was investigated in West Germany (DiNardo and Pischke, 1997). The empirical results from DiNardo and Pischke are shown in Table 3.1, above. The empirical results show that workers who used pencils and pens received a wage premium similar to those individuals using a computer. However, the analysis is based upon three cross sectional data sets, and whilst the pencils and pens coefficient is stable across all three periods, as evident from Table 3.1, the coefficient on computer usage grows - indicating its increasing importance.

Further potential problems of such correlations between technology indicators and wages are that the technology indicator is correlated with unobservable skills. If the measure of computer usage is positively correlated with some unmeasurable dimension of an individual's skill, then it may not be technical change (as measured by computer usage) that has caused the premium to rise. Rather, the unobserved skill has become more important over time. Indeed, recent empirical evidence suggests that this may well be the case in the United States (Murnane, Willett and Levy, 1995). By using two longitudinal data sets based upon the same individuals over time (*National Longitudinal Study of the High School Class of 1972* for the 1972 cohort and *High School and Beyond* for the 1980 cohort), Murnane et al (1995) find that cognitive skills have become more important. In particular, for males the coefficient on mathematics score for those graduating in 1980 is almost three times as large as the comparable coefficient in 1972. Recently, similar evidence has been produced in the United Kingdom (Harmon and Walker, 1997). Ability measures throughout different empirical specifications were found to be of significance, with a large role for maths ability in influencing earnings (Harmon and Walker, 1997). However, contrary to the above evidence Green (1998) finds that numerical skills have no significant impact upon wages for men or women. A possible reason for the conflicting research findings is that Green (1998) controls for the use of computing, whereas Harmon and Walker (1997) and Murnane et al (1995) do not. Computers are associated with large impacts upon pay for both men and women, at 13 per cent and 18 per cent respectively (Green, 1998). Indeed, when controls for computer usage are excluded the impact of numerical skills becomes significant. Thus it appears that computing and numerical skills are correlated, suggesting that the previous findings of positive impacts of numerical skills upon pay may possibly be only picking up the effects of computer usage.

A possible way of controlling for unobservable skills in individual earnings functions is to employ firm level data. Figures from the United States by Doms, Dunne and Troske (1997) using plant level data, give more robust evidence of possible endogeneity bias than DiNardo and Pischke (1997) show. The results from cross sectional analysis (*Survey of Manufacturing* and the *Worker Establishment Database*) show that the plants using more sophisticated equipment employ more skilled workers. Those workers who use such equipment receive wages in the order of 8 per cent to 20 per cent higher than the workers in the least technologically advanced plants. Although this evidence suggests that there is a positive relationship between the level of technology and earnings, it is possible that the technology indicator is correlated with some omitted variable (as above). Indeed, by including characteristics of employees in the firm level earnings function and using longitudinal analysis (based upon the *Census Bureau Longitudinal Research Database*), it appears from the results of Doms, Dunne and Troske (1997) that this is the case. They find that technologically advanced plants paid their workforce higher wages, prior to adopting new technologies. This implies that the commonly observed cross sectional correlation seen between wages and technological use, even at the firm level, may be due to time invariant unobserved worker characteristics.

The problem of direct tests of the skill-technology correlation is that it is difficult to take account of the endogeneity of technical change. One way of attempting to control for such empirical problems is to model both wages and technology simultaneously by instrumental variables. In the United Kingdom the relationship between establishment level wages and technology has been investigated by estimating the determinants of wages and technology simultaneously (Chennells and Van Reenen, 1997). Employing cross sections of the *Workplace Industrial Relations Survey* for 1984 and 1990, Chennells and Van Reenen (1997) find that, after controlling for endogeneity bias, the impact of new technology upon wages is seriously upwardly biased. Their conclusions suggest that higher quality workers are more likely to be matched with new technologies.

3.2.2.2 Skill-biased technological change : Production/cost functions

So far, it has been demonstrated that modelling the skill-biased technology hypothesis by employing wage equations is prone to a number of empirical problems. Another way of analysing the strength of the technological change hypothesis is to examine the quantity side (rather than the prices, as with the above studies looking at wages - technology), by employing production or cost functions using firm or industry level data. A common econometric specification based upon the firm rather than the individual employs cost functions to assess the degree of technological change. Take a cost function for the *f*th production unit in year *t* as

$$C\left[\left(W^{s}_{ft}\right),\left(W^{u}_{ft}\right),K_{ft},Y_{ft},Q_{ft}\right] \tag{3.4}$$

where W^{s} is the skilled wage rate, W^{u} is the unskilled wage rate, K is capital, Y is output, and Q is an indicator of technology. Based upon the assumption that $C[.]$ has a translog form (Berndt, 1990), it is possible to derive a skilled wage bill share equation for 3.4 :

$$S_{ft} = \beta_0 + \beta_1 t + \beta_2 y_{ft} + \beta_3 k_{ft} + \beta_4 \left(\frac{w^{s}}{w_{u}}\right)_{ft} + \lambda q_{ft} \tag{3.5}$$

Where lower case letters denote natural logarithms, t is a time trend allowing changes in the share over time, and S is the share of skilled wages in total wages, $S = \left[w_{s} - \left(w_{s} + w_{u}\right)\right]$. Given that it is likely the same firm is followed over time, first differencing the above share equation 3.5, and then adding an error term, results in the following econometric specification :

$$\Delta S_{ft} = \beta_1 + \beta_2 \Delta y_{ft} + \beta_3 \Delta k_{ft} + \beta_4 \Delta \left(\frac{w^{s}}{w_{u}}\right)_{ft} + \lambda \Delta q_{ft} + \varepsilon_{ft} \tag{3.6}$$

This type of specification can be used to empirically test reasons for changing factor cost shares over time. In empirical practice it is likely that the relative wage term $\left(\frac{w^{s}}{w^{u}}\right)$ is not exogenous and so is usually excluded. The common measure of technology, q, in the literature has been Research and Development expenditure. Such a specification is estimated in the United States, based upon firm level data at the three digit level, from the *Annual Survey of Manufacturing* (Berman, Bound and Griliches, 1994). The results from Berman et al (1994) imply that over the period 1979 to 1987 a one percentage point increase in Research and Development expenditure increases the annual share, S, by roughly 0.1 per cent. Similar results are found in the United Kingdom (Machin, 1996[b]), using firm level data from the *Workplace Industrial Relations Survey* (WIRS). Machin finds that over the period 1982 to 1989 a one percentage point rise in Research and Development expenditure increases the wage bill share by 0.07 per cent.

Evidence from both sides of the Atlantic has shown evidence of a positive and significant correlation between technology and factor shares. Although this type of methodological approach is not prone to the empirical problems of estimating earnings functions such as in equations 3.2 and 3.3, as described above, the measures of technical change are not perfect. Research and Development is criticised as being a poor measure of technological change, because expenditure has fallen in the 1980s and early 1990s in some OECD countries (Machin and Van Reenen, 1998).

Table 3.2 Research and Development Intensity in Manufacturing Industries

	1973	*1979*	*1981*	*1985*	*1989*	*1991*
United States	0.0634	0.0642	0.0765	0.0965	0.0868	0.0860
United Kingdom	0.0428	0.0548	0.0634	0.0615	0.0603	0.0596

Machin and Van Reenen, 1998, Table 1, page 27. Research and Development intensity defined as Research and Development expenditure as a proportion of value added.

However, much of this fall is due to the reduction in government funded Research and Development. For example, in the United Kingdom and the United States the Peace Dividend has translated into much less government financed military expenditure. The decline in the level of Research and Development intensity is apparent over this period (Machin and Van Reenen, 1998), and is reproduced in Table 3.2, above. In the United

Kingdom intensity fell after 1981, and in the United States intensity fell after 1985 (based upon OECD data in national currencies).

In an attempt to overcome the problems associated with Research and Development intensity, empirical evidence at the firm level has used different measures of technology. A common alternative proxy for technological change has been a measure of computer investment as a percentage of total investment as a proxy for q in equation 3.6 above. Evidence for the United States gives similar results to the Research and Development measure, where a one percentage point increase in computer investment results in a 0.28 per cent increase in the share S (Berman, Bound and Griliches, 1994). An indicator of the introduction of computers into the workplace for the United Kingdom is available in WIRS, and again a strong positive association with the wage share is found (Machin, 1996[b]). Further evidence for the United Kingdom of the impact of computer usage is based upon 80 three digit industries. Looking at employment shares, rather than wage shares, the impact of computing is found to be in the region of 14.4 per cent (Haskel, 1996). Haskel and Heden (1999) use firm level data and find that skill upgrading is driven by within establishment changes in skill composition and that computerisation reduced the demand for manual labour. The finding of within establishment skill upgrading is evidence against the trade hypothesis.

The above evidence has been based upon the notion that skilled labour and capital are complementary, although it is possible that technology is positively correlated with unskilled labour or with both skilled and unskilled workers (Chapter Two, section 2.3.2). Recent evidence suggests that the demand based hypothesis favouring the skilled may be overstated (Nickell and Bell, 1996). In particular most European countries have experienced a significant increase in unemployment not only amongst the less skilled in the population, but also within the higher skill endowed (Nickell and Bell, 1996). Consequently, wage and unemployment movements are inconsistent with the hypothesis that demand shocks outweighed supply shocks in the same direction. Moreover, the experience of the United Kingdom is more consistent with skill neutral shocks which have disadvantaged both the skilled and unskilled.

Having discussed the empirical findings of the demand based theories, the following considers the role for supply side factors - female participation and immigration. As with the trade based explanation, if female participation or immigration has increased the supply of low skilled labour, hence depressing its price, then firms should have substituted to the cheaper labour resource. However, contrary to theoretical expectations, the evidence suggests that firms did not substitute high-skilled to less-skilled labour (Gottschalk and Smeeding, 1997). It is possible that both groups actually raised the demand for skilled labour, if either group is a substitute for the unskilled. That is, an increase in female participation or immigration results in an increase in the demand for skilled labour. Given such a scenario, the supply change would lead to the witnessed shift in demand for skills. The following investigates whether female participation or immigration may have increased the supply of low-skilled labour, or to what extent substitution occurred.

3.2.3 Empirical evidence of substitution possibilities

Initially, the hypothesis that an increasing supply of female workers or immigrants can result in a rise in the supply of unskilled workers is analysed. Secondly, evidence for possible substitution effects of the two groups is discussed.

In Great Britain, over the period 1973 to 1988, evidence from the *General Household Survey* suggests that the ratio of females to males who hold a degree rose from a quarter in

1974/76 to one half in 1986/88 (Schmitt, 1995). Similarly, employing data from the *Family Expenditure Survey* from 1973 to 1993, research has found that females have had a significant impact upon inequality. Moreover, amongst married or cohabiting couples the poverty rate in 1991 would have been approximately 50 per cent higher, had it not been for women's income (Harkness, 1996). For full-time females the pay gap has been closing and by the 1990s the education gap between the sexes had disappeared (for those full time employees under 35 years of age). In fact, full-time females actually increased their educational attainment relative to that of males. Thus it is possible that there has been a general increase in the supply of skilled labour. The argument that the increase in the supply of skilled labour has risen as a result of female workers is most persuasive in the service sector, where there has been a demand shift from manufacturing to the services. From 1971 to 1994, employment in manufacturing fell from 36 per cent to 20 per cent, whilst that in the service sector rose from 20 per cent to 73 per cent (Harkness, 1996). Consequently, the argument that females have increased the supply of low-skilled labour, hence depressing the wages of the low skilled, appears unfound.

Considering the impact of immigrants upon wage levels, it is possible that the supply of skilled labour relative to unskilled labour has contracted. As a high proportion of immigrants to the labour market are less skilled than natives, this may contribute to the decline in the pay of less-skilled workers. For Great Britain, using data from consecutive cross sections of the *General Household Survey* over the period 1973 to 1992, it has been reported that the most disadvantaged group of immigrants are blacks who have spent much of their working lives abroad (Bell, 1997). Whilst the difference between natives' and immigrants' wages falls over time, it remains negative (Bell, 1997). For white immigrants, income converges to that of natives within a short space of time, where in general such immigrants have on average more years of schooling than natives. Hence, in Great Britain the effect of immigration upon supply depends on the relative supply of black to white immigrants. If the relative supply is greater than unity, then the supply of skilled workers relative to unskilled labour contracts, and if less than unity the supply of skilled workers relative to unskilled labour expands.

Possible substitution effects between immigrants/females and low-skill endowed males can be estimated, by incorporating a measure of the share of female/immigrants in an earnings function :

$$\omega_i = X_i\delta + \left(\frac{z}{n}\right)\pi + \varepsilon_i \tag{3.7}$$

where the earnings, ω_i, of individuals born in the country are regressed upon observable characteristics X_i and the share of females/immigrants $\left(\frac{z}{n}\right)$ in the economy (z represents the number of females/immigrants and n is the population size). If π is negative, then this suggests that females/immigrants are substitutes to low-skilled labour. Employing a similar methodology to that in equation 3.7, Topel (1994) found that in the United States high-skilled women compete with low-skilled men, and the degree of substitutability between the two groups is high. The decline in the relative wages of the low-skilled males to other male skill groups, over the period 1972 to 1990, can be largely attributed (91 per cent) to rising supplies of high-skilled females. Possible problems with this type of analysis is that women have a greater likelihood of working with computers than men (Krueger, 1993). This can help to explain the rise in the supply of females and implies that skill-biased technological change is the root cause (Blau and Kahn, 1997). Rather, an increase in the supply of females is not the cause of any earnings dispersion found, instead the origin is skill-biased technological change where females are more likely to work with such innovations.

Adopting the above equation 3.7 to examine the impact of immigrants on the wages of young Austrian workers, it was found that a 1 per cent increase in the share of foreign workers increases natives' wages by 2.1 to 3.7 per cent in 1991 (Winter-Ebmer and Zweimuller, 1996). This suggests that immigrants are complements to low-skilled labour, rather than substitutes. Evidence from the United States, based upon the same methodological approach, finds that immigrants and natives are substitutes (Borjas, Freeman and Katz, 1996). Using data for 1980 and 1990 from *Public Use Samples of the Census of Population* Borjas et al (1996) found that a rise in immigration reduced the wages of males by -0.0173 log points in 1980 and increases them by 0.2869 log points in 1990. This implies that in the earlier period immigrants were substitutes, but by the 1990s they are complements to low-skilled males. However, it is possible that there may be omitted variables correlated with wages and immigrants that cause the sign to change.

3.3 Institutional changes

Evidence of the impact of falling collective bargaining upon the wage structure is available from decomposition analysis, individual level data (both cross sectional and panel), plant level data, and time series analysis.

Firstly, based upon decomposition analysis, it is possible to decompose the variance of earnings into a weighted combination of union and non-union sector variances, plus an interaction term based on the union earnings gap, as follows (based upon Gregg and Machin, 1994):

$$V(W) = \left[U \times V(W^u)\right] + \left[(1-U) \times V(W^n)\right] + \left[U \times (1-U) \times (W^u - W^n)^2\right] \qquad \textbf{(3.8)}$$

where U is the proportion of establishments with recognised unions and $V(W^k)$ is the variance of log earnings for group k (k=u,n where u denotes union presence and n denotes no union). The first two terms in square brackets pick up within-sector changes in the structure of earnings, whilst the final term captures between-sector changes due to trade union related wage differentials. This type of approach has been employed in the United Kingdom (Gregg and Machin, 1994), using establishment level data from the *Workplace Industrial Relations Survey*. Over the period 1980 to 1990, it is found that the impact of declining union structure can be associated with an 18 per cent rise in the earnings of the semi-skilled.

Further evidence is available by employing cross sectional data based upon the individual to investigate the impact of union status upon earnings. Such an approach uses regression techniques to consider the premium associated with belonging to a union. Consider the following empirical model :

$$\omega_i = \phi_0 + D_i\phi_1 + X_i\phi_2 + \varepsilon_i \qquad \textbf{(3.9a)}$$

$$\omega_i = \theta_0 + D_i\theta_1 + X_i\theta_2 + UN_i\theta_3 + \varepsilon_i \qquad \textbf{(3.9b)}$$

where ω is log earnings, D is a dummy for the relevant skill group, X includes a set of explanatory variables, and UN indicates that the individual belongs to a union. If, as is hypothesised, the decline in unionisation contributed to the rise in skill differentials, the inclusion of the union dummy, as in equation 3.9b, should lead to a lower estimate on the skill dummy.

Table 3.3 Effect of unionisation upon earnings differentials for males

Workers	*Change in differential from regressions*		*Change due to fall in union density*	
	No union	*Union*	*Absolute*	*Per cent*
Ages 25 to 64				
White-collar/blue-collar	0.07	0.04	0.03	48
College/high school	0.06	0.05	0.01	16
Ages 25 to 34				
White-collar/blue-collar	0.11	0.06	0.05	45
College/high school	0.10	0.08	0.02	18

Freeman (1993), Table 4.3, page 144. Based upon equations 3.9a and 3.9b

That is, since unionism reduces skill differentials, the coefficient on the dummy skill variable in the equation controlling for unionisation (equation 3.9b) should be larger than the coefficient in the equation without a dummy (equation 3.9a), so $\theta_2 \rangle \phi_2$. This methodology is adopted to consider the impact of falling unionisation in the United States over the period 1978 to 1988 (Freeman, 1993). Table 3.3, above, shows the results gained by Freeman (1993). In the first column, estimates of the 1978–88 change in differentials when unionism is excluded are shown. Column two includes unionism, column three reports the difference between columns one and two, and the fourth column measures the impact of declining unionisation upon differentials. The results are based upon the *Current Population Survey* and suggest that roughly 40 per cent of the growth in the skills gap (white-collar - blue-collar labour) is due to the fall in union density.

Evidence of the impact of unionisation on earnings dispersion in the United Kingdom is available from establishment level data (Gosling and Machin, 1995). The advantage of establishment level analysis is that it is possible to control for plant characteristics, which are unobservable in individual based data sets and may be correlated with union presence. They use repeated cross sections of the establishment level database, the *Workplace Industrial Relations Survey* in 1980, 1984 and 1990. For plants which recognise union presence for the purpose of collective bargaining the distribution of earnings tends to be more compressed (Gosling and Machin, 1995). For those establishments which recognise union presence the standard deviation of wages for unskilled workers is 13 per cent lower than the non-union standard deviation, and 19 per cent lower for skilled workers than the non-union standard deviation. Also, over the period 1980 to 1990, the decline in unionisation is associated with around 15 per cent of the increase in the dispersion of semi-skilled earnings (Gosling and Machin, 1995). Extending the analysis into the 1990s, using cross sectional data upon individuals, it has been found that the rise in earnings dispersion would have been approximately 40 per cent less, had the rate of union recognition remained at its 1983 level (Machin, 1997).

The idea that declining trade union power has resulted in greater wage dispersion, both between and within industries, can also be examined from time series data. Indeed, some have argued that the skill-biased technological change hypothesis is inconsistent with historical facts (Leslie and Pu, 1995, 1996). Because of de-industrialisation, the United Kingdom already had a declining proportion of manual labour early in the 1970s, before the usage of computers in the workplace and *computer numerically controlled* machinery got underway. However, it is feasible that *numerically controlled* machinery, receiving data input through paper tape or punched card, was adopted before the mid 1970s and so could have started to displace the unskilled. Following the methodology of Borjas and Ramey (1994), Leslie and Pu (1995) seek to find a cointegrating relationship between earnings dispersion and variables designed to capture the various competing theories. Using data for the United Kingdom from a variety of sources, over the period 1970 to 1993, they find that the key variable in explaining the trend in earnings dispersion is institutional change - specifically falling union density (Leslie and Pu, 1995). That is, only union density is cointegrated with earnings dispersion.

3.4 Conclusion

The present chapter has discussed the empirical results arising from tests of the competing theories. As the literature stands the technological change hypothesis would appear to be the theory most favoured by economists and has been subjected to rigorous testing – controlling for ability, endogeneity bias etc. However, there has recently been a surge in the amount of research into the globalisation hypothesis. Whilst the evidence appears to be mixed, it is hard to ignore the role of trade completely. A long time advocate of the globalisation hypothesis has been Adrian Wood, who recently advanced the supposition that although technology caused the initial shock to the relative demand for skilled labour it is globalisation that has influenced the pace of the shock (Wood, 1998). If this is the case then this means that over time globalisation is becoming more important in influencing earnings dispersion. The approach adopted in this study (once controls have been made for observable worker characteristics) should be able to capture this phenomenon, in that if Wood (1998) is correct any change in the trend of globalisation will be captured by the time series analysis of cointegration (see below). Institutional changes to the labour market are also given a large weight in the literature in explaining the trend in earnings dispersion. Whilst changes in labour market pay setting, notably the move towards decentralised bargaining, have probably been significant in influencing earnings dispersion I believe that the main suspects are technology and trade.

Considered to be of central importance is gaining a measure of within-group earnings dispersion, that is, dispersion purged from the influences of workers' characteristics observable in the data used. It is important to control for individual characteristics such as experience and education as changing rewards to such factors could influence the trend in earnings dispersion over time. One of the most common methodologies used to split earnings dispersion into between-group and within-group components, has been to apply human capital models (Juhn, Murphy and Pierce, 1993; and Machin, 1996[a]). In particular, this study follows the same avenue, estimating earnings functions to purge earnings' from the influences of workers' characteristics. This is adopted over a period of 23 years for four industries (due to consistency over time – discussed in Chapter Five). The majority of the literature has focused upon particular years, or a subset of yearly observations to test competing theories, which is evident from this review. However, considered to be of primary importance to this study is how within-group earnings dispersion has been influenced by technological change, globalisation, female participation, immigration, and institutional changes over the past two decades. The best way to do this is to apply time series methods, specifically cointegration analysis. To the extent this has done in the past (Leslie and Pu, 1995, 1996 for the United Kingdom), the measure of earnings dispersion has not been purged of workers' characteristics, and furthermore the analysis has been carried out at an aggregate economy-wide level, not by industry.

Chapter Four sets out the empirical framework derived from two empirical strands in the literature – cross sectional controls for individual characteristics Juhn, Murphy and Pierce, 1993; Schmitt, 1995; Machin, 1996; and time series analysis – Borjas and Ramey, 1994; Buckberg and Thomas, 1996; and Leslie and Pu, 1995, 1996. The framework is then used to test what has caused within-group earnings dispersion and discusses why the approach adopted is considered superior to the alternatives.

4

A Two Stage Approach

4.1 Introduction

The distinction between earnings dispersion arising **between** and **within** specific groups is one grounded in the literature reviewed in the previous chapter. This means that once controls for the influence of individuals' characteristics have been made, for instance education the remaining residual is interpreted as unobserved skill. Rising earnings dispersion within-groups defined by education and experience is an observed characteristic of the British labour market in recent years (Gosling, Machin and Meghir, 1996). The current chapter introduces the empirical approach used in this study to decompose earnings dispersion into its two prospective components. Previous research has found that the variance of the unobserved skill (or residual) has risen over time (Schmitt, 1995). Once controls have been made for individual characteristics the remainder is analysed in terms of the factors identified in the literature review. This approach is adopted in each of the four industries. In the **first** step micro-economic data based upon the individual is used to control for differences across the population in experience, education, personal characteristics and regional location - all of which may influence earnings. The **second** stage uses time series techniques, based upon aggregate industry data, in an attempt to explain the trend in the within-group component over time in terms of the factors discussed in Chapter Two. The two stage approach is advantageous for the following reasons :

1) It overcomes the problem of aggregation bias discussed in section 4.2 below;

2) Various problems were identified when attempting to model the theoretical impact of market forces and institutional change. For example, measuring skill-biased technological change by a technology indicator is prone to endogeneity bias. This arises by employing an equation such as 3.2 in Chapter Three, where there is a reliance upon micro data. A two step approach overcomes this problem, where influences upon earnings can be controlled for in the first step, and then the competing theories can be analysed by examining trends in the data at the industry rather than the individual level. As discussed in the next section, this overcomes the problems based upon relying solely on micro econometrics.

An industry level examination of earnings dispersion will provide evidence as to whether the same influences have played a common role across industries, or whether each industry is affected differently by technology and trade etc. A reason to suspect that each industry will react differently to the demand and supply influences is that firstly each industry may have different levels of substitution between low skilled labour and technology. Consequently, technological change will influence those industries where the rate of substitution or ease of swapping lower skilled labour for technology is greater. The same rationale can be given to the impact of females and immigrants upon earnings dispersion, again their role will depend upon the degree of substitution between low skilled labour and females/immigrants. Each industry may have had a history of different levels of institutional rigidities upon pay, consequently any change in pay setting arrangements can be expected to have distinct impacts by industry even if the rate of institutional change is the same across industries.

4.2 Problems envisaged of data pooling

The fact that disaggregated data is used to control for individual characteristics - gaining a measure of within-group dispersion by industry - and more aggregated industry level data is used to explain its trend means that pooling the data can result in serious problems. Consider the following:

$$\omega_{ijt} = X_{ijt}\alpha + Z_{jt}\varsigma + \varepsilon_{ijt} \tag{4.1}$$

where there are *i=1....n* individuals, *j=1....J* industries and *t=1....T* time periods. The expression on the left-hand side, ω_{ijt}, is the logarithm of earnings, which is regressed on a vector of individual characteristics X_{ijt} and a vector of industry characteristics Z_{jt} over time. The fact that the industry level variables have no *i* subscript in equation 4.1 has important implications. Specifically, individuals in the same industry may share some common component of variance which cannot be entirely attributed to either individual specific characteristics or industry factors. In such a situation, the error components ε_{ijt} from equation 4.1 will be positively correlated across people from the same industry. This results in the conventional standard errors of the estimated industry effects ς to be significantly downwardly biased, and is commonly known as aggregation bias (Moulton, 1986, 1990).

Aggregation bias can be overcome by taking averages over individuals by industry *j* in period *t*. From the above equation, this implies:

$$\tilde{\omega}_{jt} = \tilde{X}_{jt}a + Z_{jt}b + e_{jt} \tag{4.2}$$

where $\tilde{\omega}_{jt}$ represents average log earnings in the market and $\tilde{X}_{jt}$ is a similar average of observed individual characteristics. Equation 4.2 can be estimated using industry by year cell means where "~" denotes a cell average. Assuming that there is no correlation between the unobserved determinants of earnings across industries, the residuals in equation 4.2, e_{jt}, are uncorrelated across observations. Under this scenario the standard errors are valid. In principle, the coefficients estimated by this procedure should be equal to those from equation 4.1, that is, $\alpha = a$ and $\varsigma = b$. All that should differ are the sampling errors, that is, $\varepsilon \neq e$.

Using cell means itself presents an awkward problem. There is a possibility that the data in equation 4.2 may differ in orders of integration, that is, in the stationarity of the data. Stationarity is an important concept within time series econometrics because the standard regression model makes assumptions about the stationarity of the disturbance term, as well as the stationarity of the variables in the regression. In particular, the standard regression model assumes that the errors are drawn independently from a white noise process, and that the independent variables are random stationary processes - independent of the residual. A trended variable is a typical case of a non-stationary process where regressing a mixture of trended and non-trended variables against one another is likely to result in a spurious regression.

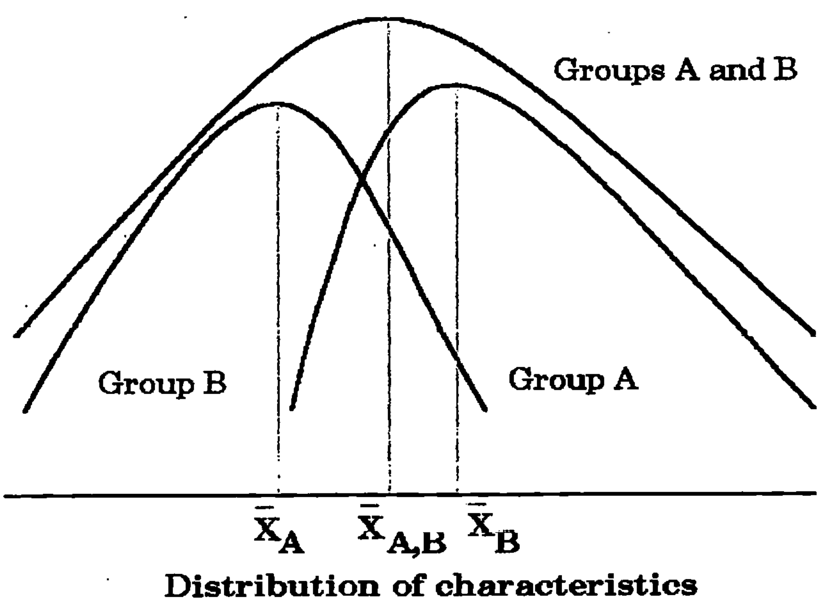
Owing to the problems associated with data pooling, the analysis that follows proceeds in two separate stages. **Firstly**, estimation upon individual micro level data, and, **secondly**, estimation upon industry data.

4.3 Step One : Decomposing earnings dispersion by industry

One problem with existing studies is that the measure of earnings dispersion used is typically a ratio of the average earnings of one relatively skilled group to that of a less-skilled group. For example, using the ratio between the top and bottom deciles of the earnings distribution as an inequality measure is common (Gosling, Machin and Meghir, 1994).

Similarly, Machin (1996[a,b]) considers the share of employment, or earnings, of manual to non-manual workers. This type of measure raises the issue that any inference about the determinants of inequality assumes an equal distribution of human capital and personal characteristics across the population. Consider that the economy consists of two groups of individuals, group **A** and group **B**. Figure 4.1, below, gives a hypothetical example of the problem associated with simple ratio measures of earnings dispersion. The distribution **A,B** shows the situation where both group of individuals have the same average set of characteristics, that is, $\overline{X}_{A,B}$. Now consider the case where the two groups of individuals **A** and **B** have a different distribution of personal characteristics. In such a situation $\overline{X}_A \langle \overline{X}_B$ and so group **A** has a lower set of average characteristics than that of group **B**. Consequently, the two groups of individuals have an unequal distribution of characteristics. This means that any dispersion observed in earnings may be due to such factors.

Figure 4.1 Hypothetical distribution of two group's characteristics



The approach adopted in the first step compensates for this by deriving a measure of earnings dispersion free from human capital effects and regional factors. A regression framework is used to control for specific individual characteristics, such as : experience, employment status, colour, education and regional location, following Schmitt (1995) and Machin (1996[a]). Accumulated human capital determines workers' productivity and the latter influences relative earnings. Under such a scenario, within-group earnings dispersion can be seen as the dispersion of the residual from the regression, where a wider dispersion of the residuals shows greater earnings dispersion occurring within-groups (Machin, 1996[a]). Consequently, a measure of earnings dispersion is derived which is purged of personal, educational, experience and regional influences. Any remaining earnings dispersion is important to understand, as the literature suggests that the majority of earnings dispersion occurred within narrowly defined groups (Juhn, Murphy and Pierce, 1993; Schmitt, 1995; Machin, 1996[a]). The earnings equation estimated thus takes the following form:

$$lnW_i = \omega_i = \lambda + \beta \mathbf{Exp}_i + \gamma \mathbf{Exp}_i^2 + \sum_{q=1}^{3} \theta_q \mathbf{D}_{iq} + \sum_{g=1}^{6} \mu_g \mathbf{Ed}_{ig} + \sum_{h=1}^{10} \eta_h \mathbf{Region}_{ih} + \varepsilon_i \quad \textbf{(4.3)}$$

where there are *i=1...n* individuals, ω_i is the logarithm of the gross weekly earnings, experience takes a parabolic shape, the intercept λ accounts for potential earnings in period *0*, and the vector **D** includes personal characteristics of the individual given as colour, marital status and part-time or full-time employment status. The vector **ED** consists of six educational dummy variables giving the highest level of educational attainment where such dummies outperform the years of schooling variable (Chapter Five), and the vector **Region** is ten dummy variables to identify the region the individual lives in.

The earnings function in 4.3 is estimated for each industry *j=1...J* and over time *t=1...T*, thus, ∀j,t. There are 23 yearly observations and 4 industries, so 92 cross sectional equations are estimated. The following simplifies the above equation 4.3 into matrix format:

$$\omega_i = X_i\delta + \varepsilon_i \qquad \forall j,t \ \textbf{(4.4)}$$

$$\varepsilon_i \sim \text{IID}(0,\sigma^2)$$

The interpretation given to the residual ε_i from an equation based upon the above, is that, after controlling for personal characteristics, educational endowments, experience and regional location, the standard deviation represents within-group earnings dispersion. Between-group earnings dispersion reflects changes that have occurred to the returns in X_i in the *j*th industry at time *t* and is given by the standard deviation of the estimated wage as:

$$v(\hat{\omega}) = \sqrt{\sum_{i=1}^{n}\left[\frac{(\hat{\omega}_i - \hat{\bar{\omega}})^2}{n-1}\right]} \qquad \forall j,t \ \textbf{(4.5)}$$

Similarly, within-group earnings dispersion in the *j*th industry at time *t* is given by the standard deviation of the residual and is that part of earnings which cannot be explained by changing returns to X_i :

$$v(\hat{\varepsilon}) = \sqrt{\sum_{i=1}^{n}\left[\frac{(\hat{\varepsilon}_i - \hat{\bar{\varepsilon}})^2}{n-1}\right]} \qquad \forall j,t \ \textbf{(4.6)}$$

where a caveat indicates the coefficient is an estimate, thus $\hat{\omega}_i = X_i\hat{\delta}$ and $\hat{\varepsilon}_i = \omega_i - \hat{\omega}_i \equiv X_i\left(\delta - \hat{\delta}\right)$. We now have a scalar measure of within-group earnings dispersion for each industry and time period. The objective of the first step is to decompose overall earnings dispersion into between-group and within-group effects for each industry.

4.4 Step Two : A time series investigation to determine what drives earnings dispersion within groups for each industry over time

The second stage of the analysis uses time series techniques to consider the impact of market forces and institutional changes on within-group earnings dispersion for each industry, following Borjas and Ramey (1994), Leslie and Pu (1995, 1996) and Buckberg and Thomas (1996).

Initially, it is important to know whether the underlying stochastic process that generated the data can be assumed to be invariant with respect to time. That is, are the measures of within-group earnings dispersion derived from equation 4.6, technological change, globalisation, female participation, immigration and institutional change stationary processes. If the characteristics of the stochastic process change over time, it will often be difficult to represent the time series using a simple regression. Moreover, a single equation regression model in which within-group dispersion is related to market forces and institutional change assumes that the structural relationship described by the equation is invariant over time - that is, stationary. If the trend in the data is non-stationary i.e. contains a unit root, then simple regression techniques should not be used to model earnings dispersion. This is because modelling non-stationary data by standard regression techniques (Ordinary Least Squares - OLS) will often result in spurious correlations. Any significant relationship found between within-group earnings dispersion and potential explanations are likely to be of a contemporaneous nature, rather than being meaningful, causal relations.

Suppose that we believe that a variable y_t, which has been growing over time, can be described by the following autoregressive relationship:

$$y_t = \rho y_{t-1} + \Theta_t$$

where $\Theta_t \sim IID(0, \sigma^2)$. This can be re written as:

$$(1-\rho L)y_t = \Theta_t$$

where L is a lag operator (i.e. $Ly_t = y_{t-1}$, while $L^2 y_t = y_{t-2}$, and so on). By forming a characteristic equation :

$$(1-\rho L) = 0$$

then if the roots of this equation are all greater than unity in absolute value, y_t is stationary. In other words, stationarity requires that $|\rho| < 1$, that is, I(0). To test the hypothesis that the data series y_t is a stationary process, the common test to apply is the Augmented Dickey Fuller (ADF) test, Dickey and Fuller (1979), based upon:

$$\Delta y_t = \psi_0 y_{t-1} + \sum_{i=1}^{n} \psi_i \Delta y_{t-i} + \mu + \pi T + \Theta_t \tag{4.7}$$

The test allows for deterministic components in the form of a constant μ and a trend T to influence the data generating process. Stationarity is tested by the hypothesis that $\psi_0 = 0$, against the alternative $\psi_0 \langle 0$. If the null hypothesis is accepted, then the data contains a unit root and so is non-stationary.

Much of the literature has sought to explain fluctuations in wage relativities by analysing data that has been first differenced or detrended. However, this type of analysis removes the trend component, where clearly the long term persistent movements of the trend in relative wages is of importance. By first-differencing data researchers are only analysing year-to-year growth rates. The argument made here is that the best way to proceed is to analyse the levels of the relevant variables, rather than their differences. Once the first stage of the empirical approach has been implemented, all the data used in the second stage (within-group earnings dispersion, technological change, globalisation, female participation, immigration and institutional change) should be checked for stationarity using equation 4.7, above.

The multi-variate cointegration method developed by Johansen (1988)[1] can be used for assessing which of the potential explanatory factors has the largest impact upon earnings for each industry. To determine which variables to include in the multivariate system we, use a bi-variate approach based upon Engle and Granger (1987) to see which of the potential factors were cointegrated with within-group earnings dispersion. The bi-variate approach is based upon the following:

$$v(\hat{\varepsilon})_t = z_t\beta + \kappa_t \qquad \forall j \quad \textbf{(4.8)}$$

where the vector **z** is defined as consisting of the technological change, globalisation, female participation, immigration and institutional change measures respectively. Estimation using Ordinary Least Squares gives an idea of the long run steady state relationship between the variables in the model, and because it is a bi-variate model all dynamics and concerns about endogeneity can be ignored. To test the hypothesis that $v(\hat{\varepsilon})$ and **z** are cointegrated, the residual κ is tested for unit roots, that is, whether it is a stationary process by applying the Augmented Dickey Fuller test (ADF), based upon the above equation 4.7. That is, the hypothesis that $\psi_0 = 0$ is tested against the alternative, $\psi_0 \langle 0$. If the null hypothesis is rejected, then this indicates that within-group earnings dispersion $v(\hat{\varepsilon})$ and **z** cointegrate. Those variables which are cointegrated with within-group earnings dispersion are included

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[1] A possible problem that may be envisaged of the two step approach, is that for the second step we only have twenty-three observations, yet time series models typically use hundreds of observations. Recent work Reimers (1992) suggests that by using small sample sizes the null hypothesis of no cointegration is over rejected. However, this can be compensated by taking into account the number of parameters to be estimated in the model and making an adjustment for the degrees of freedom when computing the trace statistic and the maximal eigenvalue test statistic - see equations 4.14 and 4.15, below.

in the overall system. Thus, defining $\mathbf{y}_t$ as a vector of the within-group inequality measure derived from the first step, see equation 4.6, $v(\hat{\varepsilon})$, technological change (**TC**), globalisation (**G**), female participation (**FP**), immigration (**IM**) and institutional change (**IC**), we have as time series data for each of the 4 industries:

$$\mathbf{y}_t = \left[v(\hat{\varepsilon}), \mathrm{TC}, \mathrm{G}, \mathrm{FP}, \mathrm{IM}, \mathrm{IC}\right]_t' \tag{4.9}$$

where $\mathbf{y}_t$ is an unrestricted vector auto regression (VAR) of endogenous variables. The data can be reformulated into a vector error correction model (VECM):

$$\Delta \mathbf{y}_t = \Gamma_1 \Delta \mathbf{y}_{t-1} + \ldots + \Gamma_{q-1} \Delta \mathbf{y}_{t-q-1} + \Pi \mathbf{y}_{t-q} + \eta_t \tag{4.10}$$

where $\Gamma_d = -(\mathrm{I} - \mathrm{A}_1 - \ldots \mathrm{A}_d)$, *d=1...q-1*, and $\Pi = -(\mathrm{I} - \mathrm{A}_1 - \ldots \mathrm{A}_q)$. The estimated matrix can be decomposed as $\Pi = \alpha\beta'$, where α and β are *(m×r)* matrices and *r* is the number of cointegrating vectors. The matrix β contains all the cointegrating vectors of the system. Re-writing the above equation 4.10 as

$$\Delta \mathbf{y}_t + \alpha\beta' \mathbf{y}_{t-q} = \Gamma_1 \Delta \mathbf{y}_{t-1} + \ldots + \Gamma_{q-1} \Delta \mathbf{y}_{t-q-1} + \eta_t \tag{4.11}$$

the Johansen method corrects for short run dynamics by alienating their impact. This is achieved by regressing $\Delta \mathbf{y}_t$ and $\mathbf{y}_{t-q}$ separately on the right-hand side of equation 4.11. Consequently, two $(n \times 1)$ vectors of residuals are obtained, $\mathbf{R}_{0t}$ and $\mathbf{R}_{qt}$, from the following:

$$\Delta \mathbf{y}_t = \Phi_1 \Delta \mathbf{y}_{t-1} + \ldots + \Phi_{q-1} \Delta \mathbf{y}_{t-q+1} + \mathbf{R}_{0t}$$

$$\mathbf{y}_{t-q} = \Xi_1 \Delta \mathbf{y}_{t-1} + \ldots + \Xi_{q-1} \Delta \mathbf{y}_{t-q+1} + \mathbf{R}_{qt}$$

From this, four *(n×n)* matrices $\mathrm{S}_{00}, \mathrm{S}_{0q}, \mathrm{S}_{q0}, \mathrm{S}_{qq}$ are constructed from the second moments and cross products of $\mathbf{R}_{0t}$ and $\mathbf{R}_{qt}$ as:

$$S_{ab} = T^{-1}\sum_{a=1}^{T} R_{at}R_{bt}^{'} \qquad a,b=0,q \tag{4.12}$$

The maximum likelihood estimate of β is obtained as the eigenvectors corresponding to the r largest eigenvalues from solving the equation

$$\left|\lambda S_{qq} - S_{q0}S_{00}^{-1}S_{0q}\right| = 0 \tag{4.13}$$

This gives n eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$ and the corresponding eigenvectors $\hat{V} = (\hat{v}_1, \ldots, \hat{v}_n)$. If the cointegrating matrix β is of rank $r<n$, the first r eigenvectors which determine linear combinations of stationary relationships can be given as $\hat{\beta} = (\hat{v}_1, \ldots, \hat{v}_r)$.

To test the null hypothesis we employ both the trace statistic and the maximal eigenvalue statistic. Because the analysis used in this study only has 23 observations, it is possible that the test statistics may be subject to sample size distortions, which can result in an over rejection of the null hypothesis (Reimers, 1992). To correct for this problem associated with small samples, Reimers (1992) suggests weighting both the trace statistic and maximal eigenvalue statistic by the sample size after adjusting for degrees of freedom, hence $T - nk$, where T is the sample size, n is the number of variables in the model, and k is the lag length. A test of, at most, r cointegrating vectors amounts to:

$$H_0: \hat{\lambda}_a = 0 \qquad a=r+1, \ldots, n$$

where only the first r eigenvalues are non zero, and $\hat{\lambda}_{r+1}, \ldots \hat{\lambda}_n$ are the $n-r$ smallest canonical correlations. This restriction can be employed for different values of r and then the log of the maximised likelihood function for the restricted model ($LR_{restricted}$) is compared to the log of the maximised likelihood function of the unrestricted model ($LR_{unrestricted}$), and a standard likelihood ratio test computed. Hence, the null hypothesis is tested using firstly the trace statistic:

$$\lambda_{trace} = -2\log(Q) = -[T - nk]\sum_{a=r+1}^{n} \log\left(1 - \hat{\lambda}_a\right) \quad r=0,1,2,...,n\text{-}2,n\text{-}1 \qquad (4.14)$$

where $Q = \frac{LR_{restricted}}{LR_{unrestricted}}$. Another test of the significance of the largest λ_r is the maximal eigenvalue or λ_{max} statistic:

$$\lambda_{max} = -[T - nk]\log\left(1 - \hat{\lambda}_{r+1}\right) \qquad r=0,1,2,...,n\text{-}2,n\text{-}1 \qquad (4.15)$$

This amounts to a test that there are *r* cointegration vectors against the alternative that *r+1* exist.

The existence of multiple cointegrating relationships implies that *r>1* where any linear combination of the columns of β is also a valid representation of the equilibrium relationships. Normalising the within-group earnings dispersion measure in the β matrix leads to:

$$\beta = \{1, \phi_1, \phi_2, \gamma_1, \gamma_2, \tau\} \qquad \forall j \quad (4.16)$$

where 1 is the normalised coefficient on within-group earnings dispersion $v(\hat{\varepsilon})$, ϕ_1 is the coefficient on technological change (**TC**), ϕ_2 is the coefficient on globalisation (**G**), γ_1 is the coefficient on female participation (**FP**), γ_2 is the coefficient on immigration (**IM**) and τ is the coefficient on institutional change (**IC**). In other words, the cointegrating relationship that we are interested in is where within-group earnings dispersion is defined by:

$$v(\hat{\varepsilon})_t = \phi_1(TC)_t + \phi_2(G)_t + \gamma_1(FP)_t + \gamma_2(IM)_t + \tau(IC)_t \qquad \forall j \quad (4.17)$$

Table 4.1 Testing the competing theories in the literature

Absolute size of coefficients	*Outcome*
If $\lvert\phi_1\rvert > \lvert\phi_2\rvert$, $\lvert\phi_1\rvert > \lvert\gamma_1\rvert$, $\lvert\phi_1\rvert > \lvert\gamma_2\rvert$ and $\lvert\phi_1\rvert > \lvert\tau\rvert$	Then technological change is the main cause of within-group earnings dispersion
If $\lvert\phi_2\rvert > \lvert\phi_1\rvert$, $\lvert\phi_2\rvert > \lvert\gamma_1\rvert$, $\lvert\phi_2\rvert > \lvert\gamma_2\rvert$ and $\lvert\phi_2\rvert > \lvert\tau\rvert$	Then globalisation is the main cause of within-group earnings dispersion
If $\lvert\gamma_1\rvert > \lvert\phi_1\rvert$, $\lvert\gamma_1\rvert > \lvert\phi_2\rvert$, $\lvert\gamma_1\rvert > \lvert\gamma_2\rvert$ and $\lvert\gamma_1\rvert > \lvert\tau\rvert$	Then female participation is the main cause of within-group earnings dispersion
If $\lvert\gamma_2\rvert > \lvert\phi_1\rvert$, $\lvert\gamma_2\rvert > \lvert\phi_2\rvert$, $\lvert\gamma_2\rvert > \lvert\gamma_1\rvert$ and $\lvert\gamma_2\rvert > \lvert\tau\rvert$	Then immigration is the main cause of within-group earnings dispersion
If $\lvert\tau\rvert > \lvert\phi_1\rvert$, $\lvert\tau\rvert > \lvert\phi_2\rvert$, $\lvert\tau\rvert > \lvert\gamma_1\rvert$ and $\lvert\tau\rvert > \lvert\gamma_2\rvert$	Then institutional change is the main cause of within-group earnings dispersion

Table 4.1, above, shows how the competing theories capable of explaining within-group earnings dispersion can be tested. By comparing the relative sizes of the coefficients, we can shed light on the possible determinants of earnings dispersion occurring after controls have

been made for different distributions of personal characteristics, education and experience across the population. What is of interest in this study is whether the same factors are significant in each of the 4 industries. To date, the majority of the research in the United Kingdom has either been for the economy as a whole or manufacturing industries (Leslie and Pu, 1995; Schmitt, 1995; Machin, 1996[a,b]). Because three of the industries considered in this study are outside of manufacturing, it is a possibility that each industry experienced different impacts as discussed in the introduction – section 4.1.

4.5 Conclusion

The methodology employed uses both cross sectional econometrics based upon earnings functions and time series techniques to analyse the trend in variables. The first stage is used to purge earnings dispersion from differing returns to personal characteristics, education and experience, all of which may influence the trend in dispersion over time. The main objective of the second step, and the principal result of the research, is to find out which factors - demand, supply or institutional change - are the most significant in influencing within-group earnings dispersion for each industry.

A two step approach is also not subject to some of the potential empirical problems identified in Chapter Three. A prime example of this is the problem of endogeneity bias associated with entering indicators of technical change into an earnings function (Chapter Three, section 3.2.2). The two step approach is not prone to this problem because the possible causes of any remaining earnings dispersion after the first stage are modelled from a macro econometric perspective. By adopting time series techniques to discover the influences behind within-group dispersion, not only are endogeneity issues irrelevant, but also the empirical testing in the second stage is not dependent upon economic theory.

Rather, the results of the second stage are data driven and this is used to consider what has the largest impact upon earnings dispersion. Consequently, empirical problems of modelling the determinants of earnings dispersion using micro econometrics are avoided.

5

Data Requirements for the Empirical Analysis

5.1 Introduction

The current chapter describes the data required to carry out the empirical work. Micro data based upon the individual is required for the first step of the procedure, to gain a measure of earnings dispersion purged from differences in workers' characteristics. The second stage employs aggregate data at the industry level in an attempt to explain the trend in any remaining earnings dispersion over time. The principal source of data in this study is the annual General Household Survey (GHS) for the years 1973 to 1995. Not only is the GHS used to create a measure of within-group earnings dispersion by industry, but measures of supply are also derived from the data.

The GHS is a government sponsored survey conducted continuously throughout the year on households in England, Scotland and Wales. It provides detailed information on individuals and their families. The twenty-three annual versions of the GHS vary substantially from one another. Variables change and definitions alter over time. The meanings of the coded computer responses change and even the sample size varies significantly. Section 5.2 explains in detail the procedures used to create a consistent data set of labour market variables from the GHS and the problems encountered. Section 5.3 describes the data sources used to proxy market forces and institutional change by industry. Supply variables in the form of female participation and immigration are calculated from the GHS, whilst demand and institutional change proxies are available from different sources. The sources of data for the demand indicators are the OECD's ANBERD data set giving information on research and development expenditure, a proxy for technological change. International trade is proxied by import and export movements over time, taken from the OECD STAN data set. Both R&D and trade are deflated by value added from the OECD STAN data set. Finally, the number of workers involved in strikes is used to proxy institutional change. These data are available from the International Labour Organisation.

5.2 Micro data based upon the individual

The GHS data posed a number of obstacles when attempting to create a consistent series of data over time. Of particular importance are changing definitions of earnings, and industrial classification changes at the one digit level. The following considers these topics in turn: labour force status, earnings definitions, labour force skills (education and experience), matching of industries over time, personal characteristics and regional indicators.

5.2.1 Labour force status

The GHS allows for the definition of at least three labour market states over the period 1973 to 1995 : "employed", "unemployed" and "economically inactive". Respondents are classified as employed if they have done paid work for any number of hours during the week prior to the GHS interview. The unemployed are all of those individuals out of work, but looking for employment in the week preceding the interview.

This includes those waiting to take up a job and those who are sick or injured, who would otherwise have been seeking active employment. Respondents not satisfying either of the above two underlined categories are termed economically inactive.

For the purposes of implementing the first stage of the empirical procedure, only those individuals qualifying as employed are considered. The employed group is split into those individuals who are employees and those who are self employed. Only those individuals who are employees holding a single job are considered. Otherwise this will inflate earnings dispersion by comparing an employee with a single job to an employee with more than one job. Following previous work in the literature, only employees are considered in order to keep the group of individuals as comparable as possible (Schmitt, 1995; Machin, 1996[a,b]).

5.2.2 Changing earnings definitions

The wage variable used in the analysis is the logarithm of the gross weekly wage deflated to 1973 prices by the Retail Price Index. Wages are deflated from nominal terms in order to take account of inflation over time. A particular problem with this variable over the period 1973 to 1995 is that there have been several changes to the design of the questionnaire. For the years 1973 to 1978, respondents were asked to record both their earnings over the previous twelve months and the number of weeks in employment. Before 1979 the following questions were asked of employees:

-*On what date were you last paid a wage or a salary?*
-*How long a period did your last wage or salary cover?* and
-*What was your gross pay last time before any deductions were made?*

The above questions were used to construct weekly earnings including wages, salaries, tips, bonuses and commissions. After 1979 weekly earnings were estimated as the usual gross earnings received, inclusive of tips and bonuses per pay period, from each individual's main job divided by the number of weeks covered in each pay period. Any comparison of earnings over the two time periods may be affected by the definition change. However, previous research (Schmitt, 1993) has found no discontinuity. Moreover, the GHS data is found to be consistent with that from the New Earnings Survey (NES) when comparing trends in the bottom, top and median percentiles. In the United Kingdom, the NES covers approximately 1 per cent of the population giving earnings data on more individuals than any other data.

The other change occurred in 1992. The GHS income section was revised to improve the response to this section and thus classify more informants by their income. A report by the Office for National Statistics (ONS, 1992) found that the mean gross weekly income of individuals in 1992 was £177. This figure compared to one of £179 in 1991. Included in the statistics after 1991 are two groups of respondents with estimated incomes. There were 1,482 respondents in 1992 who estimated at least one component (earnings, interest or dividends) of their own income and 767 interviewed by proxy. Neither of these two groups would have been included in the pre 1992 samples. Excluding those individuals with estimated incomes for 1992 produced an almost unchanged mean income of £176. Although the mean is slightly lower than that of 1991, the difference is not statistically significant. Figure 5.1 plots the consistency of the GHS data from 1987 to 1995 in comparison to the NES for the same period (following Schmitt, 1993). The plots of the data for the bottom decile, the median and the top decile show the data to be consistent over the period. That is, each decile follows the same trend as the data in the NES.

Figure 5.1 Data plots of the bottom decile, the median and the top decile comparing the GHS and the NES

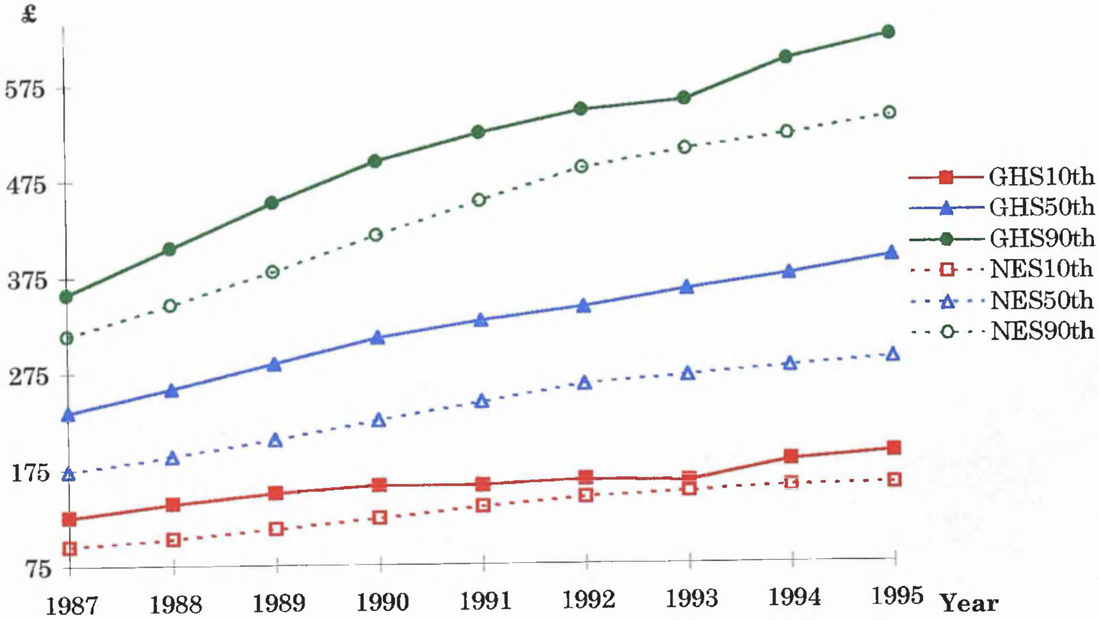
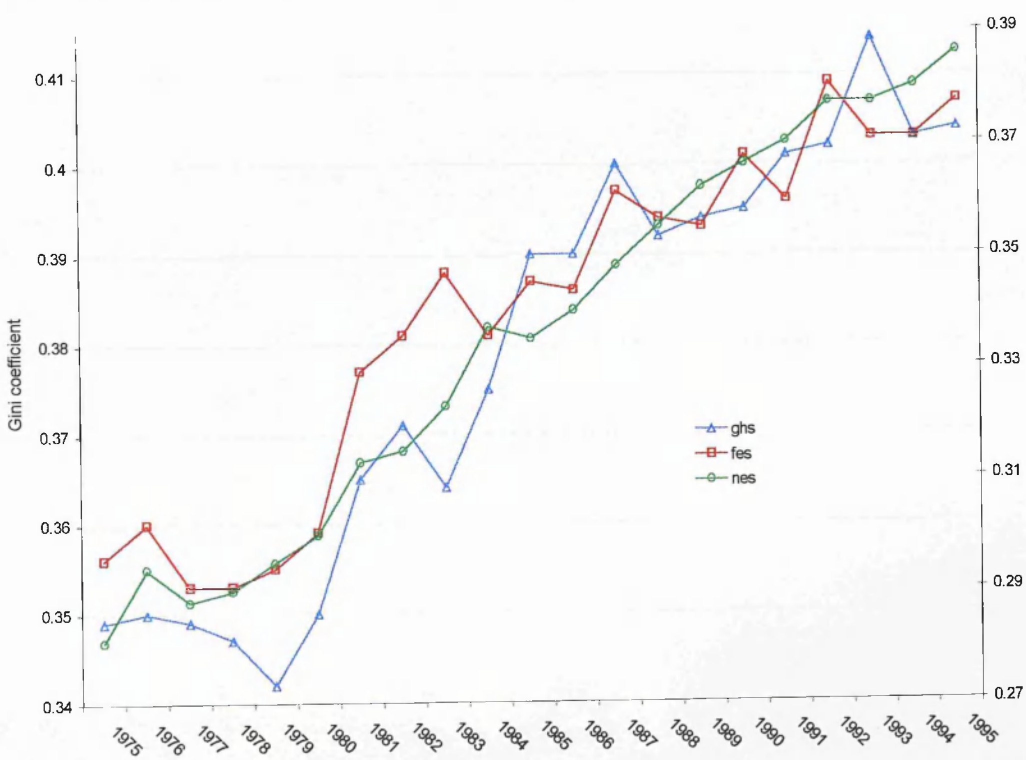


Figure 5.2 Plots of Gini coefficient for weekly earnings from GHS, FES and NES



To check the consistency of the earnings data further, figure 5.2 plots a gini coefficient of weekly earnings using data from the GHS compared to the NES and FES – using data from Machin (1998) Table 1a, pp.88. The correlation between the GHS and NES is 0.962, and the GHS and FES 0.955. In addition, it is not possible to gain a completely consistent hourly wage rate over the period 1973 to 1995. This is due to substantial changes in the data collected on the number of hours worked. A measure of hourly earnings is only available consistently for the years 1973 to 1977. As a result all analysis is based upon gross weekly earnings pre 1979 and usual gross weekly earnings post 1979.

5.2.3 Labour market skills: Education and experience

Measures of educational attainment and personal characteristics are required to control for any earnings dispersion which may arise due to differences in education, experience, colour, marriage status, employment status or regional location. The GHS has gathered information on both workers earnings and their level of education from 1973 to present[1]. Particular attention is given to the construction of education related variables. Whilst the data include conventional measures of education based upon years of schooling, this is less than satisfactory. Educational measures based upon highest educational qualification held are the preferable indicator of an individual's achievements. The empirical procedure adopted in the first stage also controls for experience, which may also influence earnings dispersion. The GHS does not ask respondents for their number of year's

[1] Although the Labour Force Survey (LFS) collects information on workers' educational attainment which is similar to that of the GHS, it does not collect earnings data. The Family Expenditure Survey (FES) asks its respondents about their level of earnings and years of schooling post 1978. However, the FES does not ask respondents about their educational qualifications. The NES gathers data upon earnings from a sample of approximately 1 per cent of British employees, but includes no information on workers' level of education. As a

experience at work. Instead, potential experience has to be calculated. Respondents are asked at what age they finished school, where school refers to primary and secondary education only, not the number of years in full-time education. If respondents continued their studies beyond school, the GHS asks at what age the individual finished their last spell of full-time education. This can lead to measurement problems if conventional formulae for determining years of schooling are adopted. For example, if years of schooling is measured as "age left full-time education minus five", then this will systematically over-estimate the years of schooling for an individual who finished full-time education after spells in full-time employment. To try to avoid this problem, potential experience is calculated as the respondent's age less their age of completing full-time education, if this was less than twenty-seven (following Schmitt, 1995; Blanchflower and Oswald, 1994). When their age was greater than this cut off there was presumably a broken spell of education and so potential experience is calculated as "age minus age left school plus three". This was done because of the number of individuals leaving full-time education (probably a degree, typically lasting 3 years, hence +3) in their forties and after.

Using educational qualifications rather than years of schooling presents several advantages, as well as avoiding the above pitfalls. In terms of earnings equations, qualification based specifications produce a higher best fit - R squared (Schmitt, 1993). Table 5.1, below, replicates the results of Schmitt (1993) for 1975 and 1985.

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result, for these reasons the GHS is deemed a superior data set to undertake the task in hand.

Table 5.1 Adjusted R squared from alternative earnings specifications[2].

Year	*Qualifications*	*Years of schooling*	*Years of schooling and square*	*Years of schooling dummies*
1975	0.335	0.285	0.317	0.307
1985	0.351	0.267	0.307	0.298
1995	0.262	0.205	0.228	0.216

The table also extends his analysis by considering 1995. For each year the qualification based specification clearly outperforms other alternatives (as found by Schmitt, 1993) in terms of the R squared. Qualifications also perform better than a specification using years of schooling and its square or twelve dummy variables for years of completed schooling. The superiority of the dummy categories of educational attainment stems from a number of factors. Firstly, the measurement of qualifications is possibly a more accurate proxy for educational achievement than that of years of schooling. This is because the GHS does not ask the total number of years in education. The second reason is that qualifications better capture changes in the demand and supply for skills for which empirical support exists (Schmitt, 1993). Thirdly, years of schooling, even if accurately measured, do not closely proxy achievement for the majority who leave at 16. In this group there is a large range of abilities and achievements. Consequently, the measures of educational attainment hereafter are based upon an individual's highest educational qualification.

[2] The dependent variable used in each specification is the log of real weekly earnings from an individual's main job. Each regression includes years of potential labour market experience, its square, a part-time dummy, a non-white dummy, a marriage dummy and ten regional indicators. The "qualifications" category adds six dummy indicators to the basic specification (see Table 5.2, below). The "years of schooling" specification replaces the qualification dummies, and the "years of schooling and square" adds the square of the variable. Finally the "years of schooling dummies" specification includes dummy variables for less than 10 years of schooling, between 10 years and less than 15, between 15 years and less than 20, and greater than 20 years of schooling.

The education groups available from the GHS consist of fifteen possible consistent categories of education attainment over the period 1973 to 1995, see appendix A1. Because wage dispersion is considered within specific industries, some of the education categories have no variation (especially post 1978 as sample sizes fell), as is evident from section 5.2.4, below. Hence it made sense to group certain categories. From the fifteen possible groups of educational levels, six educational dummy variables are derived, shown in Table 5.2, below, using the no qualifications category as the reference group.

Table 5.2 Educational dummy variables created from the General Household Survey

Educational groupings	**Description**
Degree	*Higher degree, first degree, university diploma*
Vocational Higher	*Highest vocational education group, HNC, HND, BEC/TEC, City and Guilds, or qualifications gained from professional institutions below degree standard but higher than A level*
A Level	*GCE A level, Scottish Leaving Certificate SLC, Scottish Certificate of Education SCE, Scottish University Preliminary Examination SUPE at higher grade, or Certificate of Sixth Year Studies*
O Level	*One or more GCE O levels, GCSE or CSE grade 1, and clerical or commercial qualification such as typing or shorthand*
Apprenticeships	*Miscellaneous apprenticeships*
Others	*This group includes: non-graduate teaching qualifications, nursing qualifications (e.g. SEN, SRN, SCN), middle and lower vocational qualifications, and all remaining qualifications*

In 1974 approximately 54 per cent of the labour force fell into the no qualifications category. However, by 1995 this figure had fallen to just under 31 per cent. Qualifications can be either vocational or academic. Vocational qualifications are generally earned whilst working through apprenticeship schemes, part-time study or short bursts of full-time study between employment spells. The vocational qualifications used in the GHS range from high vocational to low vocational attainment and are given in Table 5.2. The pure academic qualifications range from CSE classifications to higher degrees. The available categories are amalgamated to give six divisions, ranging from degree to others; the latter group consists of a mixture of academic and vocational qualifications and can be viewed as a catch-all category. The group with university qualifications consists of all students who successfully complete an undergraduate course as well as those individuals who go on to obtain higher degrees.

5.2.4 Matching industries over time

One of the major problems of adopting an industry level analysis of earnings dispersion over such a long period of time is that the industrial classifications used in the United Kingdom have changed. The Standard Industrial Classification (SIC) allocates to every unit of production a number denoting its major area of activity. The one digit level is the most aggregated and is that reported in the GHS. For the period that is used in the research a major change occurred to the SIC which affected the one digit definition. In 1980 industry codes fell from twenty-four groups to ten at the one digit level. Table 5.3, below, shows how the industries were matched (Appendix A4 gives a detailed account of the content of each category pre- and post-break years). The following gives details of the methodology used to find out which industries are consistent over time. Based upon the matching in Table 5.3, there are at most ten consistent sectors. Initially, the ratio of the industry sample size to the total GHS sample size, in each year, is found for the matched industries. Next, the percentage change in the ratio from the previous year is calculated.

Table 5.3 Matched industries after the change in coding

Standard Industrial Classification pre 1980	*Standard Industrial Classification post 1980*	*Industry definition (from GHS post 1980)*
1	0	Agriculture
4, 18	1	Energy and water
2, 5, 6, 13	2	Extraction of minerals and ores
7, 8, 9	3	Metal goods, engineering and vehicles
3, 10, 11, 12, 14, 15, 16	4	Other manufacturing
17	5	Construction
20, 23	6	Distribution, hotels and catering
19	7	Transport and communication
21	8	Banking, finance, etc.
22, 24	9	Other services

This is defined in the following way, where in period t for the jth industry, the industry size is given by Industry_j and the total sample GHS size of all industries as $\text{Sample} = \sum_{j=0}^{9} \text{Industry}_j$, $j=0...9$. Hence the ratio is given by $\varphi_{jt} = \text{Industry}_{jt} \div \text{Sample}_t$ and the absolute percentage change in the ratio for each industry between period t and $t+1$ is:

$$\%\Delta\varphi_{j,t\to t+1} = \left|\frac{\varphi_{jt+1} - \varphi_{jt}}{\varphi_{jt}}\right| \times 100\% \tag{5.1}$$

Those industries where the absolute percentage change, as calculated in equation 5.1, is greatest in the year of the SIC change (1980) are rejected. A small percentage change indicates that nothing much was happening to the structure of the industry. Those industries which remain are SIC0[3], SIC3, SIC4, SIC5 and SIC7, see appendix A3. It should be noted that others have matched more industries, Schmitt (1993), finding seven consistent categories and Blanchflower and Oswald (1994), finding all ten available categories to be consistent.

Table 5.4 The industry sample sizes over the period

	Manufacturing SIC3	*Other Manufacturing* SIC4	*Construction* SIC5	*Transport & Communication* SIC7
1973	1159	684	589	560
1974	1004	721	479	527
1975	1201	656	581	577
1976	1122	657	538	593
1977	1266	749	662	606
1978	1156	615	528	518
1979	660	333	260	291
1980	652	382	344	324
1981	575	355	291	320
1982	530	309	240	216
1983	458	244	213	177
1984	417	260	220	179
1985	430	279	207	237
1986	465	262	200	196
1987	449	257	206	204
1988	285	191	151	142
1989	344	167	159	145
1990	324	183	140	166
1991	296	200	168	162
1992	453	292	324	290
1993	421	250	300	256
1994	354	210	259	256
1995	517	494	448	305

[3] Even before the change in earnings definition (pre 1979), sample sizes in agriculture are small, a maximum of 126 in 1973. After 1978 the sample size depletes, to under 50 by the 1980s. Consequently, employing the first stage of the empirical anaylsis (Chapter Four, equation 4.3) with 21 dependent variables would leave few degrees of freedom and in some years none. Also, some of the binary categories employed have no variation and so the empirical specification of the first stage cannot be estimated. It is on these grounds that earnings dispersion in agriculture (SIC0) is not investigated empirically.

However, it is suggested that the above approach has highlighted possible problems with previous methods of matching. Neither study carried out any simple tests to look at potential problems.

Table 5.4, above, shows the resultant sample sizes of the consistent industries. The samples reported refer to male employees who are head of the household, in current employment and hold a single job. Clearly in comparison to the early 1970s sample sizes have fallen in each industry, although they recovered slightly in the 1990s. There is a noticeable decline after 1978, which is attributable to the change in the earnings definition, as discussed above.

5.2.5 Personal characteristics and regional categories

Personal characteristics may also be important in influencing earnings and hence earnings dispersion. For example, marital status (Neumark and Koreman, 1991), colour (McNabb and Psacharopoulos, 1981), employment status, and region of location (Goodman, Johnson and Webb, 1997).

The marriage variable divides individuals into one of six civil states: married, single, widowed, divorced, separated, or cohabiting (available only 1986 to 1988). For our purposes, two states are defined from the data: married or other. The married status is available every year, whilst the contents of the non-married category varies over time due to changing definitions in the GHS and so includes every status other than married.

The GHS assigns respondents to racial groups based upon the colour defined from the visual assessment of interviewers. In most years individuals fall into white, not white, probably white, probably not white and unseen. The categories defined for the empirical analysis are white and non-white, where the non-white category includes all groups apart from white.

It should be noted that the GHS contains more than two binary categories for both marriage status and race. For instance, consistent marriage groups are married, single, cohabiting and other. Similarly, for race, until the 1990s the only available categories were white, coloured and other. In the 1990s the race variable was disaggregated to include: white, Indian, Pakistani, Bangladeshi, Black Carribean, Black African, Chinese, Arab, mixed origin, and other. The problem is that because of the falling industry sample sizes, the analysis was limited to two dummy groups. The categories used are consistent with previous empirical work using the GHS (Blackaby, Clark, Leslie and Murphy, 1997).

Whilst the GHS reports hours worked per week, substantial changes to its definition does not make it possible to derive a measure of wages per hour, as discussed above. However, the hours worked variable is used to separate individuals into either part-time employment (less than thirty hours per week) or full-time employment (greater than thirty hours).

Regional variables available from the GHS place respondents into the eleven standard British regions according to where they live, although not necessarily where they work. These groups are broadly consistent over time (see Appendix A1) and are given as: North, Yorkshire and Humberside, North West, East Midlands, West Midlands, East Anglia, Greater London, South East, South West, Wales, and Scotland. In the empirical analysis the South East is used as the reference category.

5.3 Macro industry level data

To recap, the first stage of the procedure controls for the impact of individual's characteristics on earnings dispersion, and produces a measure of remaining earnings dispersion by industry, see Chapter Four. Attempting to explain any remaining earnings dispersion following the empirical methodology of the previous chapter, requires industry level data to proxy demand, supply and institutional change effects. In particular, proxies for technological change, globalisation, supply of females and immigrants and institutional change are needed. All except the institutional change are defined as market forces.

5.3.1 Market forces

The literature review identified the prominent theories which can explain earnings dispersion which remains after controlling for observable influences. These are technological change, globalisation and supply factors. The following describes how each market force factor was proxied.

Research and Development (R&D) expenditure data as a proportion of value added is employed as a proxy for technological change, which is consistent with existing research (Berman, Bound and Griliches, 1994; Machin, 1996[a,b]; and Machin, Ryan and Van Reenen, 1997). Data on R&D is available from the OECD's ANBERD data set 1973 to 1993, which covers a number of countries including the United Kingdom. For 1994 and 1995 R&D data was taken from the CSO Blue Book. The source for value added over the period is the OECD's STAN data set. Consistency between the OECD's ANBERD and CSO R&D data was not a problem, since the OECD data is collected from national sources. The R&D data and value added data was deflated by using the RPI index with 1973 as the base year.

Table 5.5 OECD industry coverage and classifications

ANBERD ISIC groups	*Classification description*
3000	Total manufacturing
3100	Food, beverages and tobacco
3200	Textiles, apparel and leather
3300	Wood products and furniture
3400	Paper, paper products and printing
3500	Chemical products
3510+3520+3522	Chemicals excluding drugs
3522	Drugs and medicines
3530+3540	Petroleum refineries and products
3550+3560	Rubber and plastic products
3600	Non-metallic mineral products
3700	Basic metal industries
3710	Iron and steel
3720	Non-ferrous metals
3800	Fabricated metal products
3810	Metal products
3820-3825-(part 3829)	Non-electrical machinery
3825	Office and computing equipment
3830-3832	Electrical machines
3832	Radio, TV and communication equipment
3841	Shipbuilding and repairing
3843	Motor vehicles
3842+3844+3849	Other transport equipment
3845+(part 3829)	Aircraft and aerospace
3850	Professional goods
3900	Other manufacturing
4000	Electricity, gas and water
5000	Construction
7100	Transport and storage
7200	Communications
8324	Commercial and engineering services
6000+8000+8324+9000	Other services
4000+5000+6000+7000+8000+9000	Total services
1000+2000+3000+Total services	Total business enterprise

The data for the RPI index was taken from the 1996 Central Statistics Office (CSO) Blue Book. Industry coverage is available from the OECD data, but is classified by the International Standard Industrial Classification.

Table 5.6 Matching of UK and OECD one digit industry classifications

Standard Industrial Classification (UK)	***International Standard Industrial Classification (OECD)***
3: Manufacturing	3000 Manufacturing ***minus*** (3100+3200+3300+3400+3550+3560)
4: Other Manufacturing	3900 Other Manufacturing ***plus*** (3100+3200+3300+3400+3550+3560)
5: Construction	5000 Construction
7: Transport and Communication	7100+7200 Transport/communication

This presents a potential problem in that the groupings may not be compatible with the UK's Standard Industrial Classification, as used in the GHS. Table 5.5, above, shows the International Standard Industrial Classification (ISIC) codings, which was matched to the United Kingdom's Standard Industrial Classifications for the four industries, as shown in Table 5.6, above.

Whilst the value added data is complete for Manufacturing and Other Manufacturing over the period, the STAN data base does not collect value added for Construction or Transport and Communication. Thus in this instance research and development expenditure was given as a ratio to GDP, again deflated to 1973 prices. The GDP data was taken from the Annual Abstract of Statistics. For Construction and Transport and Communication the OECD Research and Development expenditure coverage was only present every other two years before 1985, i.e. 1975, 1978, 1981 and 1983 and complete thereafter. So, for the years 1976, 1977, 1980 and 1982 no data were available on Research and Development expenditure in Construction or Transport and Communication. To try to give an estimate of the missing observations, imputed observations were calculated as the proportion of expenditure in both industries to total services R&D expenditure for the available periods. This proportion is given as $\Omega = \dfrac{\text{Industry}}{\text{Total\_services}}$, where Industry equals Construction and Transport and Communication. From Table 5.5 it can be seen that total services includes Construction and Transport and Communication. The ratio was calculated by creating a moving average of the proportion. To calculate the proportion between period *t* and *t+3* where periods *t+1* and *t+2* are missing, the method was as follows: $\Omega_{t+1} = \frac{\Omega_t + \Omega_{t+3}}{2}$ and $\Omega_{t+2} = \frac{\Omega_t + \Omega_{t+1} + \Omega_{t+3}}{3}$. Having interpolated by moving average for the missing years of observations, the Research and Development data was calculated by multiplying the ratio by total services for the missing periods.

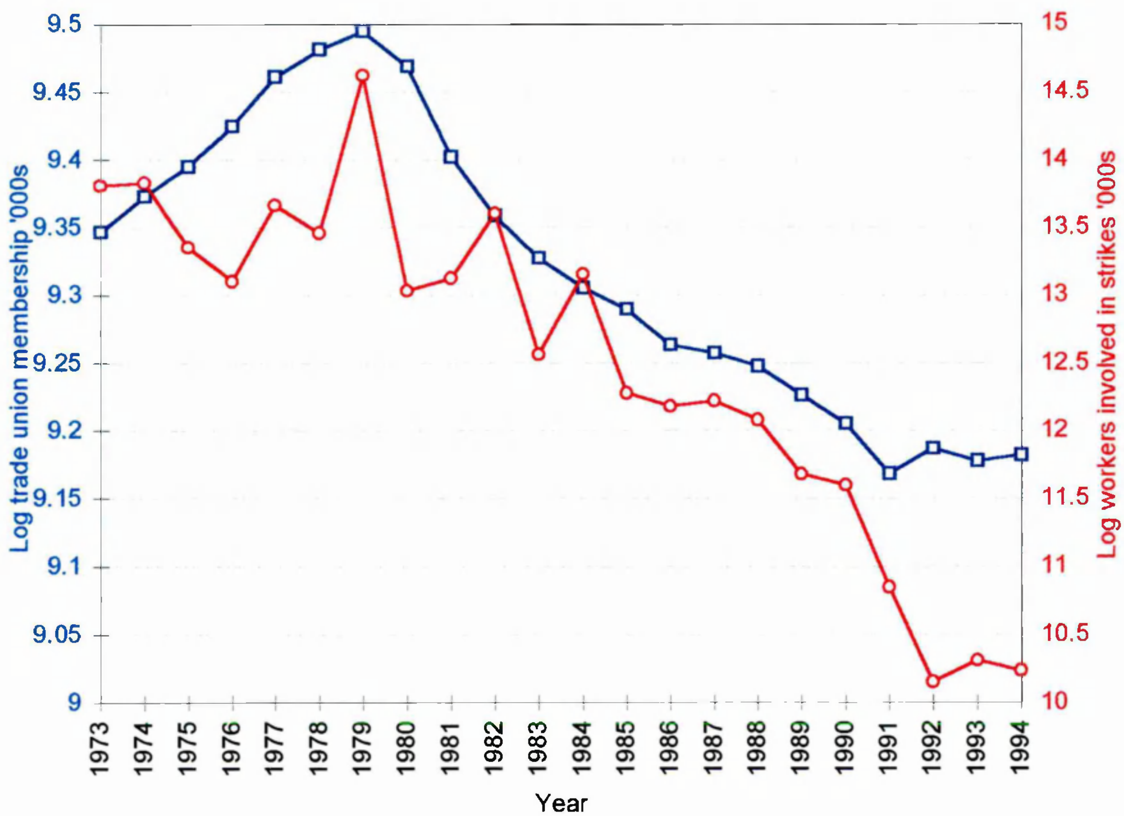
The second demand variable used attempts to assess the impact of foreign competition upon wage dispersion in the tradable goods sector. A measure of this effect is import plus export volumes as a proportion of value added (Machin, Ryan and Van Reenen, 1997), where export and import data are required. The OECD STAN data set provided the data for import and export expenditures, which was deflated to 1973 prices. Value added figures were the same as those used to construct the R&D intensity variable.

The final market force proxies included are the participation rate of females and the supply of immigrants over the period. These were derived from the GHS, where the former group consists of those women in employment as a ratio to total industry employment. The supply of immigrants was calculated as those individuals born outside the United Kingdom who were again in employment, as a ratio to total industry employment size. In both instances, being in employment was defined as working one or more hours per week. These measures of supply were available for each of the one digit industries considered.

5.3.2 Institutional change proxy

Trying to gain a measure of institutional change proved to be a relatively more difficult task than at first sight. The literature review identified trade union density or membership to be the prominent measure of institutional change in the form of the falling coverage of collective bargaining. The preferred measure to be used would have been trade union recognition, density or membership. Unfortunately, these figures are only available consistently at an aggregate level. Previous researchers (Bain and Price, 1983) have constructed industry level trade union membership and density, but only up until 1979.

Figure 5.3 Institutional change from 1973 to 1994, in terms of strikes and trade union membership



After 1979 the source of their data (Labour Force Survey) does not collect union data at the industry level for each succeeding year. Consequently, in an attempt to proxy institutional change, the number of workers involved in strikes for each industry based upon ISIC codings was used. This is available from the International Labour Organisation. Figure 5.3, above, shows how closely the trend in strikes follows that of trade union membership and the correlation between the two measures is 0.88.

Strike action represents one form of bargaining power, where a threat to strike is credible if the firm cannot replace its workforce easily. Consequently, the extent of unionisation and the ease of substitutability between union and non-union members is of importance. The analysis of the second stage uses strikes to proxy for institutional change as it follows the trend in union membership. This is consistent with previous findings (Machin, 1997).

5.4 Summary

This chapter has introduced the two types of data required to undertake the empirical analysis. In terms of the micro data based upon the individual, a number of problems have been found when attempting to create a consistent data set. The main problem associated with the industry level data was matching UK industry codings to OECD international industry codings. The major problems faced with the micro data from the GHS was changing earnings definitions and changing industry classifications. For the former, comparisons of the GHS to the NES (representative of 1 per cent of the UK population) have shown no deviations between the two series. A methodology was adopted to try to find which industries were consistent after the SIC change in 1980. Four industries were identified as being consistent, and the empirical analysis which follows is based upon these industries. The micro data is employed in Chapter Six to control for observable characteristics and to determine the amount of earnings dispersion occurring within narrowly defined groups. In Chapter Seven any remaining dispersion is accounted for by the macro data.

6

Results from Stage One - Micro Wage Dispersion

6.1 Introduction

This chapter details the results obtained from the first stage of the empirical analysis. Specifically, earnings dispersion is disaggregated into between-group and within-group elements for each of the four industries. The methodology used is as described in Chapter Four. The role of this chapter is to find out the extent to which differing returns to workers' characteristics can explain dispersion in earnings over the period 1973 to 1995. In doing so the results for each industry are contrasted with estimates available to date (Schmitt, 1995; Machin, 1996[a,b]; as described in Chapter Three, section 3.2.2.1). Questions that are addressed include how the returns to education have influenced the earnings structure over time, and to what extent personal characteristics have a role to play. Section 6.2 considers the role of workers characteristics and their influence upon earnings dispersion. However, previous research has found that a large part of earnings dispersion cannot be explained by human capital returns (Juhn, Murphy and Pierce, 1993; Schmitt, 1995; and Machin 1996[a]). Accordingly, the influence of within-group earnings dispersion upon the trend in overall earnings dispersion is also investigated. Section 6.3 looks at the model performance over time and any anomlies, whilst Section 6.4 gives details of diagnostic tests implemented to test the robustness of the earnings function over the twenty-three years for each of the four industries.

6.2 Earnings dispersion: The facts

Figures 6.1 to 6.4 show the trend in overall earnings dispersion and the contribution of between-group and within-group dispersion over time, for each of the four industries. It should be noted that adding between-group and within-group earnings dispersion does not give overall earnings dispersion; this is because each is measured in terms of standard deviation. Between-group earnings dispersion is that attributable to worker characteristics (defined in Chapter Four, equation 4.5) and within-group earnings dispersion is that due to influences occurring within groups of similar workers (equation 4.6 in Chapter Four).

In each of the four industries within-group earnings dispersion dominates between-group earnings dispersion, with the exception of Transport and Communication from 1989 to 1991. Reasons for the anomaly occurring in Transport and Communication are discussed below. This pattern of within-group dispersion dominating between-group dispersion is consistent with previous research findings (Juhn, Murphy and Pierce, 1993 for the United States; and for the United Kingdom : Schmitt, 1995; Machin, 1996[a]; Chapter Four, section 3.2.2.1). In terms of the techniques to be adopted in the second stage, what is significant is that even after controlling for the influence of workers' characteristics upon earnings dispersion, the trend in overall earnings dispersion mirrors that of within-group dispersion.

Figure 6.1 Earnings dispersion in Manufacturing

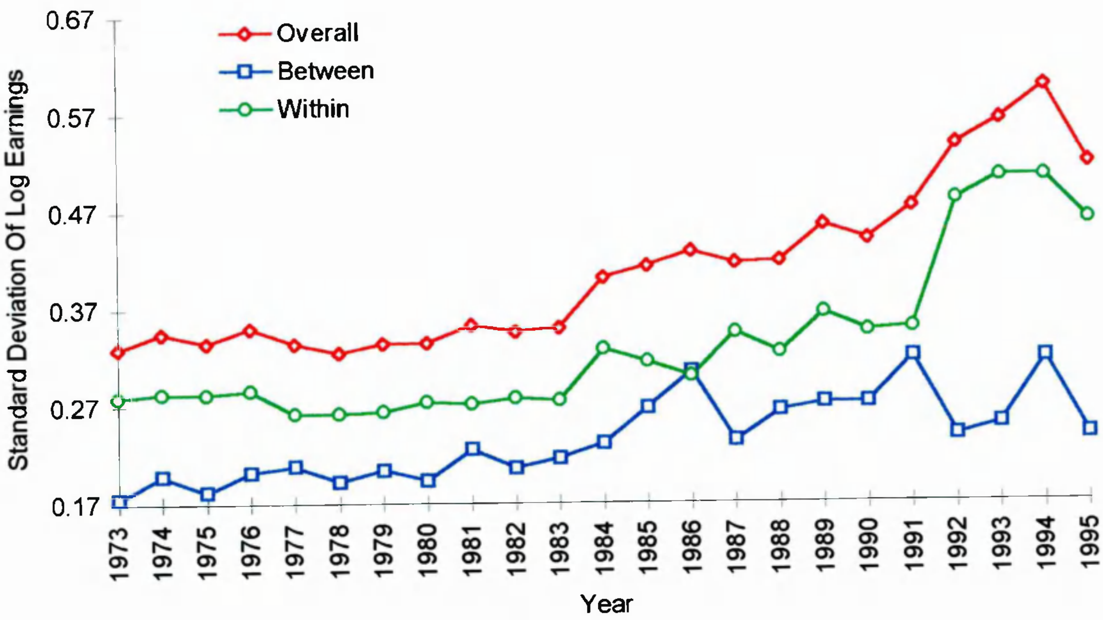


Figure 6.2 Earnings dispersion in Other Manufacturing

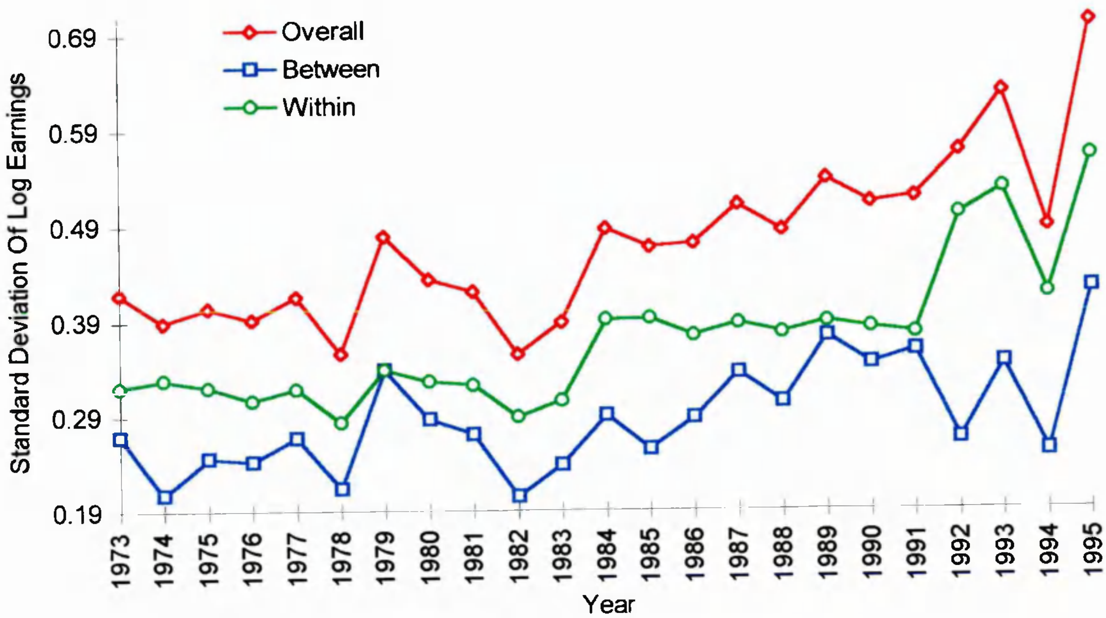


Figure 6.3 Earnings dispersion in Construction

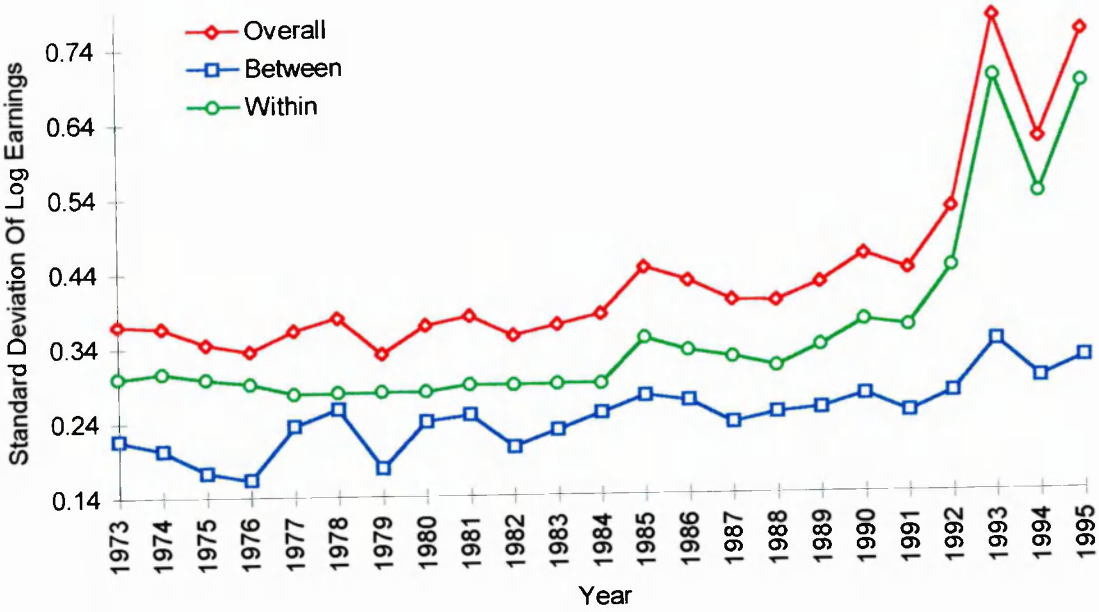
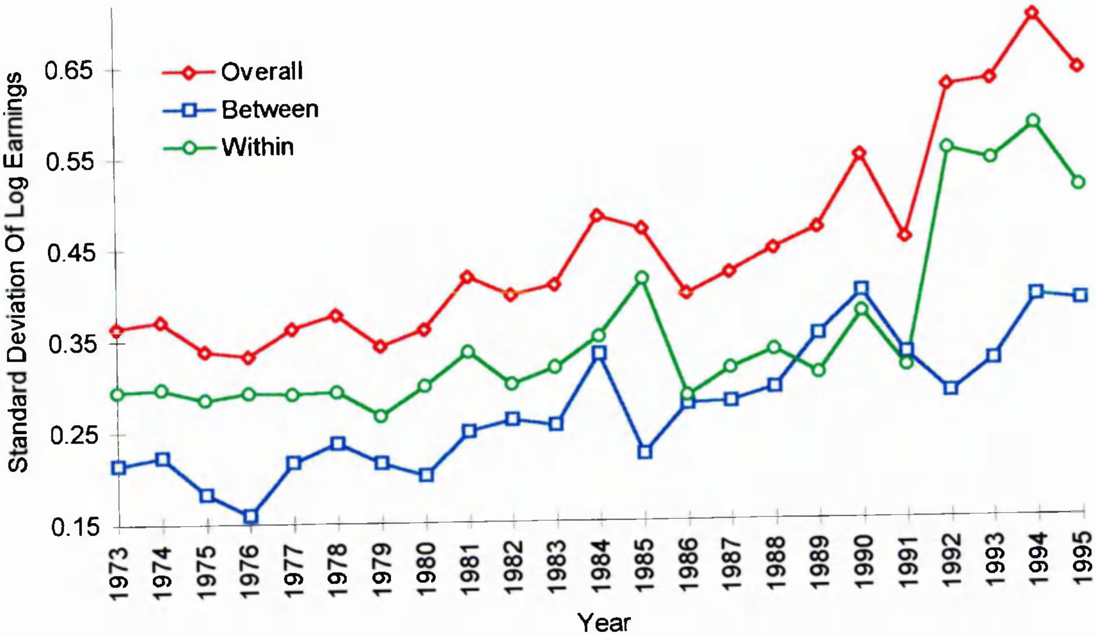


Figure 6.4 Earnings dispersion in Transport and Communication



An investigation into what influences the trend in within-group earnings dispersion is discussed and empirically tested in Chapter Seven. The remainder of the current chapter considers the role of returns to workers' characteristics and the robustness of the empirical methodology used to decompose earnings dispersion into within-group and between-group components.

As mentioned above, in each of the four industries within-group earnings dispersion dominates between-group earnings dispersion, as shown in Figures 6.1 to 6.4, with the exception of Transport and Communication. Between 1989 and 1991, Figure 6.4 shows that between-group earnings dispersion dominated. There appear to be several reasons for this phenomenon. Firstly, the premium associated with having a degree was at its highest in 1991 at 0.96 log points (Table 6.8, below), secondly, the return to higher vocational education rose from 0.32 log points in 1989 to 0.59 log points by 1991 (Table 6.8). Finally, the marriage premium was significant in 1990 at 0.16 log points (Table 6.8).

The trend in within-group earnings dispersion remained roughly constant during the 1970s and early 1980s in Manufacturing, as shown in Figure 6.1. However, this is not true in Other Manufacturing (Figure 6.2), where there is a large increase in 1979. Although the premium on A' levels was at its lowest since 1973 (at 0.20 log points, Table 6.3), there was a large increase in the returns associated with having a degree and vocational education from 1978 to 1979 (Table 6.3). Also, the difference between full-time and part-time workers was at its highest over the period 1973 to 1979 at -1.13 log points (Table 6.3). These appear to be the main factors causing between-group earnings dispersion to rise in 1979, which also influenced the trend of overall dispersion. Between 1984 and 1991, within-group earnings dispersion actually declined in Other Manufacturing. This fact is in sharp contrast to the other industries, where within-group earnings dispersion had either started to rise during the early 1980s, or remained constant. Figure 6.2 shows that for the period 1984 to 1991 between-group effects mirror the trend in overall earnings dispersion. At this time there were large increases in the return to having a degree, from 0.59 log points in 1984 to 0.87 log points by 1989 (Tables 6.3 and 6.4). Also in 1987 the influence of being non-white, and in 1989 the influence of being married, were at their greatest (Table 6.4).

As in Other Manufacturing, the trend in overall earnings dispersion from the 1970s to mid-1980s in Construction was only influenced by between-group impacts. This is most apparent in 1978 (Figure 6.3) but was not driven by rising educational premiums as in Other Manufacturing. Indeed, the returns to degrees and higher vocational education were at their lowest so far, at 0.46 and 0.22 log points respectively (Table 6.5). The premium associated with being non-white was at its lowest in 1978, at -0.08 log points (Table 6.5). These three facts would suggest that between-group earnings dispersion should have fallen, as observable skill price differentials imply. However, two factors appear to be a play. Firstly, regional location influenced between-group earnings dispersion, where those individuals living in the North West, East Midlands, West Midlands, South West and Wales the differential between each relative to the South East hit its peak in 1978 (Table 6.5). Secondly, the differential between full-time and part-time workers hit its highest peak so far, as did the differential between married to non-married individuals, at -1.11 log points and 0.18 log points respectively (Table 6.5). This is in sharp contrast to Other Manufacturing where educational differentials drove observable earnings dispersion. In the Construction industry education premiums were not responsible, rather personal characteristics mattered.

Major changes in the earnings distributions started to occur during the mid- to late 1980s in all industries. Around this time, as Figures 6.1 to 6.4 show, not only did between-group earnings dispersion increase, so did within-group earnings dispersion (although not until into the 1990s in Other Manufacturing). In Manufacturing for the years after 1983, within-group effects influenced the trend in overall earnings dispersion. This was despite increases in between-group earnings dispersion due to rising education and marriage premiums, evident from Table 6.2.

In Construction the rise in within-group earnings dispersion appeared to start after 1988, developing at a faster rate than between-group affects (Figure 6.3). Surprisingly, this occurred at a time when the returns to workers' characteristics rose. The premium for a degree was highest in 1992 at 0.88 log points (Table 6.6). Similarly, experience premiums in Construction were at their highest in 1989 at 0.05 log points, and part-time returns reached their peak in 1994 (Table 6.6). Hence, although the education and personal effects were strong during this period, something was influencing overall dispersion to a greater extent than differing returns to workers' characteristics.

Tables 6.1 to 6.8 give detailed results obtained for each of the four industries. The results shown in Tables 6.1 to 6.8 are based upon equation 4.3 (Chapter Four). Figures in italics are t statistics, which are based upon heteroscedastic consistent standard errors (see section 6.4.2, below). The final 6 rows of each table show summary/diagnostic statistics (see sections 6.3 and 6.4 for details) where:

** Significant at the 1 per cent level * Significant at the 5 per cent level.

Table 6.1 Returns to individual characteristics in manufacturing 1973 to 1984.

	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Intercept	3.20 *56*	3.23 *54*	3.22 *58*	3.24 *47*	3.02 *84*	3.29 *60*	3.30 *56*	3.29 *46*	3.13 *43*	3.25 *43*	2.16 *21*	3.32 *33*
Exp	0.02 *6.7*	0.03 *8.1*	0.02 *6.3*	0.02 *6.9*	0.03 *13.3*	0.02 *7.4*	0.03 *7.4*	0.02 *6.0*	0.03 *6.2*	0.03 *6.6*	0.01 *2.7*	0.03 *4.6*
$Exp^2 \times 100$	-0.04 *7.0*	-0.05 *8.4*	-0.04 *6.8*	-0.05 *7.4*	-0.06 *13*	-0.04 *7.9*	-0.05 *7.5*	-0.04 *5.9*	-0.05 *5.9*	-0.05 *5.7*	-0.02 *2.7*	-0.05 *4.5*
Part Time	-0.95 *3.8*	-0.94 *6.2*	-1.14 *4.1*	-1.07 *6.9*	-0.61 *3.7*	-0.85 *6.0*	-0.91 *6.3*	-0.85 *3.8*	-1.17 *3.4*	0.00 *0.0*	-0.65 *1.5*	-0.63 *1.1*
Married	0.15 *4.7*	0.01 *0.4*	0.19 *5.0*	0.10 *2.4*	0.16 *8.5*	0.08 *2.4*	0.06 *1.8*	0.09 *2.4*	0.11 *2.8*	-0.02 *0.4*	0.00 *0.0*	0.05 *0.9*
Non White	-0.08 *2.0*	-0.07 *1.3*	-0.10 *2.1*	-0.10 *2.4*	-0.04 *1.2*	-0.05 *1.5*	-0.05 *1.0*	-0.15 *4.2*	-0.09 *1.7*	-0.19 *2.8*	-0.00 *0.1*	-0.16 *2.4*
Degree	0.57 *8.3*	0.62 *7.6*	0.60 *11.3*	0.57 *9.2*	0.44 *13.1*	0.49 *10.2*	0.49 *8.0*	0.49 *8.4*	0.63 *12.0*	0.66 *12.2*	0.38 *4.9*	0.77 *9.9*
Vocational	0.34 *8.9*	0.32 *5.7*	0.27 *7.8*	0.21 *5.7*	0.29 *9.3*	0.26 *8.8*	0.20 *5.5*	0.34 *8.0*	0.31 *7.1*	0.39 *8.5*	0.20 *3.6*	0.32 *5.5*
A'Level	0.20 *6.2*	0.19 *5.6*	0.22 *5.7*	0.21 *6.5*	0.24 *8.4*	0.20 *7.2*	0.17 *5.2*	0.26 *6.3*	0.26 *6.6*	0.29 *7.6*	0.20 *3.4*	0.33 *5.1*
O'Level	0.21 *6.9*	0.24 *6.1*	0.16 *5.4*	0.20 *5.6*	0.14 *5.2*	0.16 *4.4*	0.20 *4.4*	0.23 *5.9*	0.24 *5.6*	0.21 *4.7*	0.05 *1.0*	0.14 *2.7*
Apprentice	0.07 *2.8*	0.05 *2.1*	0.10 *3.5*	0.11 *4.6*	0.07 *3.3*	0.09 *4.5*	0.09 *3.2*	0.14 *4.3*	0.09 *2.8*	0.13 *3.3*	0.05 *1.3*	0.15 *2.9*
Other	0.15 *3.5*	0.10 *2.7*	0.12 *3.2*	0.17 *3.6*	0.02 *0.5*	0.03 *0.8*	0.17 *2.8*	0.13 *3.5*	-0.01 *0.2*	0.16 *2.3*	0.15 *1.7*	0.17 *1.5*
R1	-0.07 *1.9*	-0.12 *2.9*	-0.11 *3.1*	-0.04 *1.2*	-0.08 *2.2*	-0.13 *4.0*	0.00 *0.1*	-0.07 *1.4*	0.01 *0.2*	-0.09 *1.7*	-0.10 *1.5*	-0.21 *2.5*
R2	-0.15 *4.1*	-0.06 *1.5*	-0.17 *5.2*	-0.13 *2.6*	-0.11 *3.4*	-0.11 *3.4*	-0.04 *1.0*	-0.06 *1.3*	-0.13 *2.8*	-0.10 *2.2*	-0.15 *2.0*	-0.16 *2.4*
R3	-0.07 *2.3*	-0.08 *2.3*	-0.14 *4.8*	-0.08 *2.5*	-0.07 *2.3*	-0.09 *2.5*	-0.06 *1.6*	-0.11 *2.5*	-0.04 *0.9*	-0.08 *1.3*	-0.13 *3.0*	-0.18 *3.0*
R4	-0.13 *3.2*	-0.09 *2.0*	-0.12 *2.7*	-0.09 *2.5*	-0.06 *2.0*	-0.04 *1.1*	-0.08 *1.4*	-0.10 *0.2*	-0.07 *1.8*	-0.14 *3.1*	-0.21 *3.5*	-0.18 *2.7*
R5	0.03 *1.0*	-0.04 *1.3*	-0.11 *4.8*	-0.05 *1.9*	-0.05 *2.1*	-0.10 *4.0*	-0.07 *2.0*	-0.02 *0.6*	-0.05 *1.3*	-0.05 *1.2*	-0.12 *2.3*	-0.09 *1.8*
R6	-0.14 *2.7*	-0.07 *1.4*	-0.12 *1.7*	-0.18 *3.7*	-0.10 *1.9*	-0.10 *1.7*	-0.14 *2.0*	-0.07 *1.1*	0.09 *1.0*	-0.08 *1.0*	-0.19 *2.0*	-0.04 *0.5*
R7	0.03 *0.9*	-0.01 *0.3*	-0.08 *2.2*	0.00 *0.3*	0.00 *0.0*	0.03 *0.6*	0.03 *0.7*	-0.02 *0.4*	0.09 *1.7*	-0.03 *0.3*	-0.14 *1.7*	0.00 *0.0*
R9	-0.11 *2.9*	-0.06 *1.7*	-0.15 *4.7*	-0.11 *3.6*	-0.10 *3.8*	-0.11 *3.1*	-0.12 *2.9*	-0.18 *3.6*	-0.10 *2.1*	-0.08 *1.6*	-0.07 *1.3*	-0.08 *1.4*
R10	-0.09 *2.5*	-0.05 *1.1*	-0.12 *2.7*	-0.13 *2.4*	-0.07 *2.0*	-0.19 *3.9*	-0.11 *1.2*	-0.22 *3.0*	-0.11 *1.9*	0.02 *0.3*	-0.13 *1.5*	-0.12 *2.1*
R11	-0.06 *1.8*	-0.04 *1.1*	-0.09 *2.5*	-0.11 *1.6*	-0.05 *1.6*	-0.09 *3.0*	-0.03 *0.8*	-0.06 *1.3*	-0.02 *0.3*	0.03 *0.1*	-0.08 *1.4*	-0.18 *2.1*
Obs	1159	1004	1201	1122	1266	1156	660	652	575	530	458	417
R bar sq.	0.270	0.314	0.281	0.320	0.377	0.336	0.353	0.311	0.385	0.329	0.302	0.297
DW	1.89	1.99	1.95	1.94	1.92	1.90	1.88	1.94	2.00	1.93	1.95	1.81
Hetero	76.49**	125.4**	195.5**	199.9**	117.2**	184.2**	96.64**	49.02**	59.12**	53.25**	131.3**	84.06**
Regional	11.05**	6.54*	34.89**	17.64**	12.26**	17.18**	4.66*	7.34**	1.27	4.27*	12.45**	10.10**
F(21,obs)	21.35**	22.88**	23.37**	26.07**	37.48**	28.86**	18.09**	14.97**	18.08**	13.96**	18.26**	9.35**

Table 6.2 Returns to individual characteristics in manufacturing 1985 to 1995.

	1985	**1986**	**1987**	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**
Intercept	3.41 *42*	3.45 *38.8*	3.49 *40.1*	3.54 *31.4*	3.65 *31.3*	3.43 *36.3*	3.29 *31.4*	3.88 *43.7*	3.73 *23.9*	3.29 *18.1*	3.58 *34.6*
Exp	0.03 *5.9*	0.02 *4.4*	0.03 *5.5*	0.03 *3.8*	0.03 *3.9*	0.04 *4.9*	0.03 *3.9*	-0.00 *0.5*	0.02 *1.9*	0.04 *2.9*	0.01 *1.0*
$Exp^2 \times 100$	-0.06 *5.8*	-0.04 *4.3*	-0.06 *5.2*	-0.05 *3.1*	-0.05 *3.9*	-0.07 *4.8*	-0.05 *3.2*	-0.00 *0.3*	-0.04 *1.8*	-0.06 *2.2*	0.00 *0.6*
Part Time	-1.08 *5.7*	-1.93 *5.1*	-0.80 *1.6*	-1.79 *13*	-1.16 *5.5*	-0.65 *1.5*	-1.39 *3.1*	-1.17 *6.3*	-1.14 *3.8*	-1.60 *7.6*	-0.93 *3.4*
Married	0.04 *0.8*	0.11 *2.3*	0.06 *1.2*	0.08 *1.2*	0.08 *1.5*	0.03 *0.6*	0.14 *2.1*	0.02 *0.4*	0.04 *0.4*	0.06 *1.2*	0.24 *4.5*
Non White	-0.04 *0.5*	-0.21 *4.1*	-0.26 *3.8*	-0.03 *0.4*	-0.05 *0.5*	-0.04 *0.3*	-0.04 *0.4*	-0.11 *1.4*	-0.15 *2.3*	-0.17 *2.3*	-0.16 *0.9*
Degree	0.64 *9.4*	0.59 *10.8*	0.56 *9.8*	0.66 *9.1*	0.51 *7.0*	0.79 *10.6*	0.79 *11.2*	0.45 *4.5*	0.57 *5.7*	0.81 *8.7*	0.45 *4.5*
Vocational	0.31 *5.3*	0.31 *6.7*	0.26 *5.1*	0.26 *3.9*	0.24 *3.5*	0.45 *7.2*	0.50 *8.4*	0.21 *2.4*	0.23 *2.6*	0.35 *3.6*	0.31 *4.7*
A'Level	0.26 *5.3*	0.23 *4.7*	0.28 *3.9*	0.15 *2.2*	0.29 *3.7*	0.32 *5.1*	0.49 *7.0*	0.30 *4.1*	0.15 *1.7*	0.32 *3.9*	0.29 *4.4*
O'Level	0.16 *3.2*	0.14 *2.5*	0.06 *1.1*	0.04 *0.6*	0.19 *2.9*	0.17 *2.8*	0.27 *3.9*	0.08 *1.3*	0.07 *1.0*	0.18 *2.5*	0.09 *1.6*
Apprentice	0.08 *1.8*	0.00 *0.0*	0.12 *2.2*	-0.05 *0.5*	0.07 *1.2*	0.24 *2.9*	0.16 *1.9*	0.08 *1.0*	0.05 *0.4*	0.14 *0.9*	0.05 *0.7*
Other	0.10 *0.9*	0.00 *0.0*	0.17 *1.9*	0.21 *1.9*	0.02 *0.2*	0.35 *2.5*	0.24 *1.6*	0.04 *0.5*	0.19 *1.3*	0.18 *1.7*	0.18 *2.3*
R1	-0.18 *2.6*	-0.19 *2.9*	-0.22 *3.3*	-0.21 *1.6*	-0.23 *2.9*	-0.11 *1.0*	-0.09 *1.1*	-0.06 *0.5*	-0.07 *0.6*	0.07 *0.7*	0.04 *0.4*
R2	-0.23 *3.4*	-0.07 *1.0*	-0.24 *3.5*	-0.15 *1.8*	-0.30 *3.9*	-0.18 *2.9*	-0.13 *1.5*	-0.24 *3.3*	-0.31 *2.3*	-0.16 *1.5*	-0.17 *1.6*
R3	-0.15 *2.8*	-0.12 *2.4*	-0.09 *1.6*	-0.21 *3.1*	-0.28 *4.1*	-0.10 *1.4*	-0.21 *2.5*	-0.23 *2.3*	-0.23 *2.1*	0.02 *0.2*	-0.09 *1.1*
R4	-0.17 *2.7*	-0.24 *3.7*	-0.20 *2.2*	-0.28 *4.6*	-0.27 *3.6*	-0.14 *1.8*	-0.20 *2.6*	-0.16 *1.5*	-0.19 *1.4*	0.00 *0.0*	-0.09 *1.0*
R5	-0.18 *3.4*	-0.13 *2.7*	-0.11 *2.0*	-0.19 *3.0*	-0.29 *3.7*	-0.10 *1.5*	-0.18 *3.2*	-0.10 *1.7*	-0.15 *2.0*	-0.05 *0.6*	-0.07 *1.0*
R6	-0.22 *2.4*	-0.13 *1.7*	0.00 *0.0*	-0.22 *2.6*	-0.02 *0.1*	-0.08 *1.1*	-0.02 *0.2*	0.21 *1.3*	-0.08 *0.8*	-0.16 *0.8*	-0.12 *1.3*
R7	0.01 *0.2*	0.11 *1.4*	0.05 *0.6*	-0.06 *0.5*	-0.04 *0.3*	0.05 *0.5*	-0.12 *0.7*	0.02 *0.2*	0.12 *1.0*	0.11 *1.5*	0.06 *0.6*
R9	-0.19 *3.0*	-0.08 *1.4*	-0.22 *3.7*	-0.08 *0.8*	-0.02 *0.2*	-0.01 *0.2*	-0.07 *0.9*	-0.18 *2.1*	-0.23 *2.3*	-0.08 *1.0*	-0.09 *1.1*
R10	-0.16 *1.9*	-0.30 *5.0*	-0.19 *2.8*	-0.38 *4.3*	-0.40 *4.3*	-0.08 *0.8*	0.05 *0.3*	-0.20 *1.7*	-0.18 *1.4*	-0.32 *0.9*	-0.11 *1.3*
R11	-0.05 *0.8*	-0.19 *3.2*	-0.21 *2.4*	-0.18 *1.9*	-0.35 *3.5*	-0.17 *2.5*	-0.19 *2.8*	-0.10 *1.2*	-0.30 *2.4*	-0.36 *3.0*	-0.42 *4.0*
Obs	430	465	449	285	344	324	296	453	375	354	517
R bar sq	0.388	0.486	0.279	0.349	0.315	0.339	0.413	0.157	0.149	0.239	0.178
DW	2.11	2.05	1.82	1.94	2.10	2.00	2.19	2.02	1.84	2.05	1.99
Hetero	36.16*	88.62**	153.4**	17.20	59.95**	39.00**	100.0**	97.32**	55.59**	274.6**	107.9**
Regional	15.32**	12.97**	11.26**	16.61**	16.27**	3.54	4.84*	2.99	5.61*	2.05	3.93*
F(21,obs)	13.95**	21.89**	35.32**	8.28**	8.52**	8.90**	10.88**	5.01**	4.12**	6.31**	6.33**

Table 6.3 Returns to individual characteristics in other manufacturing 1973 to 1984.

	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Intercept	3.24 *39.9*	3.13 *38.7*	3.19 *36.6*	3.12 *43.9*	2.99 *53.0*	3.39 *43.1*	3.31 *22.0*	3.26 *31.1*	3.30 *31.2*	3.25 *43.1*	1.83 *12.8*	3.31 *20.2*
Exp	0.03 *5.2*	0.03 *6.7*	0.03 *6.3*	0.03 *6.1*	0.04 *9.7*	0.03 *5.3*	0.03 *3.4*	0.03 *4.0*	0.04 *4.8*	0.03 *6.6*	0.02 *2.1*	0.04 *4.7*
Exp^2×100	-0.05 *5.5*	-0.06 *6.9*	-0.06 *6.8*	-0.05 *5.8*	-0.08 *9.7*	-0.05 *5.8*	-0.05 *3.3*	-0.05 *3.5*	-0.06 *4.8*	-0.05 *5.7*	-0.03 *1.9*	-0.08 *4.9*
Part Time	-0.96 *5.7*	-0.91 *2.8*	-0.63 *5.1*	-1.03 *12*	-0.63 *3.3*	-0.82 *4.3*	-1.13 *5.0*	-1.20 *6.7*	-0.77 *4.0*	0.00 *0.0*	-0.57 *1.0*	-0.48 *1.3*
Married	0.11 *2.5*	0.13 *3.2*	0.03 *0.5*	0.08 *2.3*	0.18 *5.9*	0.01 *0.1*	0.07 *0.9*	0.14 *2.2*	0.06 *0.9*	-0.02 *0.4*	0.18 *1.9*	-0.03 *0.3*
Non White	-0.12 *2.5*	-0.04 *0.7*	-0.06 *1.1*	-0.14 *2.6*	-0.07 *1.5*	0.05 *0.6*	-0.01 *0.2*	-0.21 *3.2*	-0.06 *0.6*	-0.19 *2.8*	-0.18 *2.0*	-0.30 *1.8*
Degree	0.79 *5.5*	0.52 *3.3*	0.47 *2.9*	0.53 *7.0*	0.62 *5.7*	0.37 *4.8*	0.55 *5.1*	0.59 *6.1*	0.77 *4.7*	0.81 *2.9*	0.36 *3.0*	0.59 *5.1*
Vocational	0.42 *4.1*	0.44 *3.9*	0.51 *5.9*	0.18 *2.3*	0.26 *2.7*	0.18 *3.5*	0.60 *4.1*	0.28 *3.3*	0.34 *3.7*	0.23 *2.7*	0.36 *3.9*	0.64 *4.6*
A'Level	0.36 *5.6*	0.27 *5.0*	0.29 *4.5*	0.27 *4.8*	0.25 *4.1*	0.20 *3.7*	0.20 *3.4*	0.28 *3.3*	0.33 *3.4*	0.41 *5.6*	0.11 *1.4*	0.28 *3.6*
O'Level	0.29 *5.4*	0.15 *3.0*	0.29 *6.1*	0.27 *5.3*	0.14 *3.8*	0.16 *4.7*	0.22 *3.4*	0.24 *4.2*	0.20 *4.2*	0.21 *2.6*	0.08 *1.1*	0.16 *2.2*
Apprentice	0.13 *3.2*	0.15 *3.9*	0.11 *2.8*	0.04 *0.9*	0.10 *2.7*	0.15 *4.1*	0.06 *1.0*	0.13 *3.0*	0.11 *2.2*	0.22 *3.5*	0.10 *1.3*	0.12 *1.6*
Other	0.16 *3.2*	0.10 *2.0*	0.18 *3.5*	0.20 *3.6*	0.06 *1.3*	0.01 *0.1*	0.32 *3.0*	0.11 *1.2*	0.20 *2.4*	-0.18 *1.4*	0.07 *0.6*	0.06 *0.3*
R1	-0.24 *3.0*	-0.17 *2.1*	-0.18 *3.1*	0.02 *0.3*	-0.15 *2.6*	-0.12 *2.7*	-0.06 *0.7*	-0.31 *4.1*	-0.07 *0.8*	0.02 *0.3*	-0.05 *0.5*	-0.35 *2.9*
R2	-0.19 *3.9*	-0.12 *2.4*	-0.13 *2.6*	-0.00 *0.1*	-0.19 *4.3*	-0.14 *2.7*	-0.14 *1.7*	-0.08 *1.3*	-0.24 *3.8*	0.00 *0.1*	-0.04 *0.5*	-0.23 *2.4*
R3	-0.20 *4.3*	-0.07 *1.5*	-0.13 *2.7*	0.00 *0.1*	-0.15 *3.1*	-0.17 *4.6*	-0.06 *0.8*	-0.15 *2.5*	-0.27 *4.4*	-0.10 *1.2*	0.00 *0.1*	-0.30 *3.8*
R4	-0.20 *3.9*	-0.13 *2.4*	-0.21 *4.1*	0.00 *0.2*	-0.16 *3.3*	-0.15 *2.7*	-0.13 *1.8*	-0.07 *1.2*	-0.26 *4.0*	0.06 *0.6*	-0.05 *0.6*	-0.17 *1.8*
R5	-0.09 *1.7*	-0.07 *1.4*	-0.01 *0.3*	-0.07 *1.3*	-0.13 *2.3*	-0.08 *1.6*	-0.26 *2.2*	-0.08 *1.1*	-0.09 *1.1*	0.07 *0.7*	-0.14 *1.6*	-0.24 *2.4*
R6	-0.19 *3.0*	-0.18 *2.0*	-0.16 *2.2*	-0.08 *1.3*	-0.23 *2.8*	-0.03 *0.5*	-0.09 *0.8*	-0.06 *0.6*	-0.13 *2.0*	-0.13 *1.4*	-0.21 *2.1*	-0.12 *1.1*
R7	-0.08 *1.3*	0.06 *1.1*	0.04 *0.7*	0.12 *2.9*	-0.06 *1.2*	0.02 *0.5*	-0.02 *0.3*	0.08 *1.1*	0.00 *0.0*	0.18 *1.7*	0.29 *2.5*	0.05 *0.5*
R9	-0.12 *2.1*	-0.16 *2.6*	-0.20 *4.2*	-0.07 *1.3*	-0.17 *3.1*	-0.16 *3.0*	-0.14 *1.7*	-0.28 *3.4*	-0.13 *1.8*	0.00 *0.1*	-0.07 *0.8*	-0.16 *1.4*
R10	-0.11 *1.0*	-0.12 *1.6*	-0.18 *2.4*	-0.07 *1.1*	-0.26 *4.2*	-0.22 *3.8*	-0.19 *2.6*	-0.30 *2.3*	-0.22 *2.3*	-0.11 *1.1*	-0.09 *0.7*	-0.38 *2.4*
R11	-0.12 *2.5*	-0.08 *1.8*	-0.04 *0.9*	0.04 *1.1*	-0.15 *2.9*	-0.16 *3.8*	-0.15 *2.2*	-0.24 *3.5*	-0.19 *2.5*	-0.10 *1.4*	-0.16 *1.8*	-0.04 *0.5*
Obs	684	721	656	657	749	615	333	652	355	309	244	260
R bar sq.	0.396	0.264	0.351	0.365	0.398	0.340	0.464	0.311	0.376	0.386	0.301	0.298
DW	1.93	1.93	1.88	1.76	1.90	1.97	2.05	1.94	1.91	2.12	2.12	2.28
Hetero	124.1**	235.3**	83.76**	74.77**	108.6**	161.7**	127.9**	49.02**	89.73**	137.5**	180.1**	196.5**
Regional	17.81**	7.58**	13.51**	0.11	20.78**	12.87**	5.10*	7.34**	10.22**	0.24	0.69	7.44**
F(21,obs)	22.32**	13.31**	17.87**	18.93**	24.51**	16.09**	14.70**	14.97**	11.17**	10.23**	17.68**	6.23**

Table 6.4 Returns to individual characteristics in other manufacturing 1985 to 1995.

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Intercept	3.27 *24.6*	3.35 *24.8*	3.19 *26.4*	3.39 *22.7*	3.15 *20.6*	3.47 *23.0*	3.28 *20.6*	3.34 *22.0*	3.64 *18.4*	3.44 *22.9*	3.49 *21.0*
Exp	0.04 *4.8*	0.05 *5.2*	0.04 *3.5*	0.04 *3.9*	0.05 *4.7*	0.04 *4.3*	0.04 *4.0*	0.04 *3.3*	0.02 *1.4*	0.03 *2.8*	0.03 *2.4*
$Exp^2 \times 100$	-0.07 *4.5*	-0.09 *5.0*	-0.07 *3.7*	-0.07 *3.3*	-0.08 *4.2*	-0.08 *4.4*	-0.07 *4.1*	-0.07 *3.4*	-0.03 *1.3*	-0.05 *2.5*	-0.04 *2.0*
Part Time	-0.48 *1.3*	-1.20 *1.6*	-0.95 *3.0*	-0.80 *1.6*	-1.12 *4.1*	-1.58 *8.5*	-0.81 *3.6*	-0.68 *2.6*	-2.29 *2.2*	-0.48 *1.7*	-1.63 *8.5*
Married	0.12 *2.2*	0.06 *0.9*	0.17 *2.0*	0.09 *1.0*	0.21 *2.4*	0.09 *1.4*	0.08 *1.2*	0.04 *0.5*	0.11 *1.1*	0.03 *0.4*	0.05 *0.7*
Non White	-0.16 *1.5*	-0.28 *3.1*	-0.50 *4.2*	-0.02 *0.2*	-0.26 *1.6*	-0.48 *3.7*	-0.26 *2.0*	-0.15 *1.6*	0.01 *0.1*	0.00 *0.0*	-0.25 *1.8*
Degree	0.59 *5.4*	0.61 *4.7*	0.52 *2.6*	0.54 *5.3*	0.87 *3.4*	0.77 *6.0*	0.77 *5.7*	0.46 *2.2*	0.49 *3.1*	0.74 *6.2*	0.79 *8.6*
Vocational	0.41 *5.8*	0.32 *2.9*	0.37 *3.3*	0.43 *4.6*	0.55 *6.8*	0.38 *3.4*	0.41 *4.4*	0.28 *2.3*	0.35 *3.4*	0.38 *3.6*	0.43 *4.9*
A'Level	0.34 *3.9*	0.30 *3.3*	0.28 *4.6*	0.38 *2.9*	0.23 *2.8*	0.27 *2.6*	0.32 *3.8*	0.40 *4.2*	0.24 *1.9*	0.29 *2.5*	0.40 *4.3*
O'Level	0.18 *2.9*	0.06 *0.7*	0.28 *3.9*	0.11 *1.5*	0.33 *3.7*	0.22 *2.5*	0.32 *3.9*	0.27 *3.5*	0.24 *2.8*	0.19 *2.2*	0.16 *1.9*
Apprentice	-0.01 *0.2*	0.04 *0.5*	0.20 *1.7*	0.11 *1.0*	0.14 *0.9*	0.09 *0.9*	0.15 *1.5*	0.12 *1.4*	0.14 *1.1*	-0.03 *0.3*	-0.18 *0.9*
Other	0.32 *2.4*	0.19 *2.5*	0.19 *1.7*	0.09 *0.8*	0.04 *0.4*	0.37 *2.6*	0.24 *2.2*	0.08 *0.7*	-0.08 *0.4*	-0.09 *0.8*	0.37 *3.7*
R1	-0.16 *1.5*	-0.18 *1.4*	-0.17 *1.2*	-0.27 *1.7*	-0.18 *1.2*	-0.07 *0.5*	0.06 *0.4*	-0.21 *1.9*	-0.16 *1.2*	-0.20 *0.8*	-0.24 *2.6*
R2	-0.26 *2.9*	-0.25 *3.0*	-0.06 *0.7*	-0.23 *1.9*	-0.17 *1.7*	-0.18 *1.6*	-0.24 *2.4*	-0.38 *2.3*	-0.53 *4.6*	-0.27 *2.5*	-0.20 *1.5*
R3	-0.21 *2.2*	-0.23 *2.7*	-0.15 *1.5*	-0.35 *3.3*	-0.28 *2.1*	-0.33 *2.2*	-0.15 *1.4*	-0.17 *1.5*	-0.19 *1.3*	-0.12 *1.0*	-0.10 *1.1*
R4	-0.14 *1.5*	-0.35 *3.9*	-0.17 *1.2*	-0.03 *0.3*	0.04 *0.3*	-0.18 *1.6*	-0.17 *1.6*	-0.15 *1.4*	-0.45 *2.0*	-0.13 *1.1*	-0.13 *1.5*
R5	-0.10 *0.9*	-0.24 *2.7*	-0.14 *1.2*	-0.29 *2.5*	-0.18 *1.8*	-0.22 *2.0*	0.06 *0.5*	-0.32 *3.2*	-0.25 *2.0*	-0.18 *1.5*	-0.06 *0.5*
R6	-0.21 *2.2*	-0.08 *0.7*	0.01 *0.1*	-0.26 *2.4*	-0.36 *1.9*	-0.22 *1.8*	-0.09 *0.6*	-0.08 *0.8*	-0.27 *2.4*	-0.12 *0.8*	-0.02 *0.1*
R7	0.04 *0.4*	-0.05 *0.5*	0.34 *3.0*	-0.01 *0.1*	0.27 *1.4*	0.03 *0.2*	0.23 *2.1*	-0.02 *0.2*	-0.15 *1.3*	-0.11 *0.9*	-0.09 *0.9*
R9	-0.25 *2.9*	-0.58 *3.7*	-0.22 *2.7*	-0.21 *2.4*	-0.58 *4.1*	-0.34 *2.6*	-0.08 *0.8*	-0.07 *0.6*	-0.14 *0.9*	-0.20 *1.7*	-0.21 *2.0*
R10	-0.32 *2.5*	-0.37 *2.6*	-0.32 *1.8*	-0.35 *2.9*	-0.19 *1.4*	-0.37 *3.4*	-0.29 *2.1*	-0.21 *1.5*	-0.35 *1.8*	-0.33 *2.5*	-0.27 *2.0*
R11	-0.16 *2.2*	-0.36 *3.5*	-0.21 *2.0*	-0.36 *3.9*	-0.17 *1.4*	-0.32 *2.9*	-0.41 *3.5*	-0.12 *1.1*	-0.24 *2.4*	-0.22 *2.0*	-0.07 *0.7*
Obs	279	262	257	191	167	183	200	292	224	210	494
R bar sq	0.239	0.317	0.377	0.318	0.405	0.376	0.413	0.157	0.226	0.185	0.333
DW	2.10	1.59	1.90	1.87	2.05	2.17	2.02	1.84	2.19	1.95	1.99
Hetero	70.34**	210.1**	132.8**	55.54**	50.88**	37.43**	25.93**	115.2**	183.1**	23.65	111.6**
Regional	7.16**	16.59**	2.49	10.00**	3.53	6.89**	1.84	1.84	6.93**	4.92*	4.28*
F(21,obs)	5.15**	6.78**	8.37**	5.23**	6.39**	6.21**	7.67**	3.59**	4.09**	3.25**	3.61**

Table 6.5 Returns to individual characteristics in construction 1973 to 1984.

	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Intercept	3.39 *38.8*	3.28 *36.4*	3.26 *45.6*	3.24 *42.2*	3.00 *59.0*	3.17 *36.6*	3.41 *34.7*	3.30 *38.2*	3.25 *32.3*	3.13 *26.4*	2.02 *18.2*	3.21 *25.9*
Exp	0.02 *4.0*	0.02 *3.9*	0.02 *4.4*	0.02 *5.0*	0.04 *9.2*	0.03 *6.1*	0.02 *4.2*	0.03 *5.7*	0.03 *4.9*	0.04 *5.2*	0.01 *2.2*	0.04 *4.9*
Exp^2×100	-0.04 *5.0*	-0.04 *4.4*	-0.04 *5.0*	-0.04 *5.2*	-0.06 *9.2*	-0.05 *6.7*	-0.05 *4.5*	-0.06 *6.1*	-0.06 *4.8*	-0.07 *5.3*	-0.03 *2.4*	-0.06 *5.0*
Part Time	-1.05 *4.7*	-0.14 *8.5*	-0.71 *2.0*	-1.09 *9.7*	-0.91 *6.9*	-1.11 *4.3*	-0.78 *3.7*	-0.86 *6.9*	-0.94 *3.6*	-0.65 *10*	0.00 *0.0*	-0.32 *1.2*
Married	0.08 *1.5*	0.09 *1.8*	0.09 *2.1*	0.10 *1.7*	0.16 *5.8*	0.18 *2.9*	0.12 *2.1*	0.07 *1.5*	0.08 *1.5*	0.09 *1.5*	0.11 *1.9*	0.08 *1.0*
Non White	-0.02 *0.4*	0.09 *1.5*	-0.08 *1.0*	-0.13 *2.4*	-0.08 *0.1*	-0.08 *1.9*	0.07 *1.0*	-0.01 *0.2*	-0.17 *2.6*	-0.20 *1.9*	-0.12 *1.9*	0.10 *0.8*
Degree	0.60 *8.5*	0.59 *7.4*	0.47 *5.1*	0.56 *8.1*	0.58 *10.7*	0.46 *8.9*	0.36 *4.5*	0.48 *9.3*	0.55 *10.8*	0.42 *6.2*	0.15 *1.6*	0.62 *6.0*
Vocational	0.34 *3.2*	0.23 *4.4*	0.31 *5.0*	0.29 *5.4*	0.34 *6.5*	0.22 *4.5*	0.16 *2.0*	0.21 *3.1*	0.36 *5.5*	0.30 *3.7*	0.07 *0.8*	0.36 *5.7*
A'Level	0.29 *4.5*	0.28 *4.2*	0.25 *3.9*	0.18 *4.1*	0.19 *4.9*	0.19 *3.1*	0.18 *3.1*	0.11 *1.8*	0.19 *3.2*	0.17 *2.3*	0.03 *0.3*	0.22 *3.0*
O'Level	0.23 *4.9*	0.25 *3.6*	0.24 *5.0*	0.25 *4.5*	0.16 *3.8*	0.08 *2.0*	0.16 *2.4*	0.12 *2.9*	0.11 *1.7*	0.11 *1.6*	0.03 *0.4*	0.09 *1.4*
Apprentice	0.06 *1.8*	0.03 *0.7*	0.09 *2.6*	0.03 *0.8*	-0.01 *0.3*	0.03 *1.1*	0.08 *1.5*	-0.01 *0.3*	0.10 *2.0*	0.11 *2.1*	-0.04 *0.8*	-0.02 *0.4*
Other	0.05 *0.9*	0.09 *1.2*	0.12 *2.1*	0.10 *2.1*	-0.06 *0.8*	-0.07 *1.2*	0.23 *2.4*	0.18 *2.0*	0.11 *0.8*	0.23 *2.1*	0.21 *3.2*	0.15 *1.0*
R1	-0.23 *4.1*	-0.06 *1.0*	-0.07 *1.4*	-0.03 *0.6*	-0.06 *1.4*	-0.12 *2.5*	-0.35 *5.1*	-0.08 *1.2*	-0.05 *0.7*	0.09 *0.9*	-0.06 *0.8*	-0.04 *0.6*
R2	-0.16 *3.0*	-0.18 *2.6*	-0.13 *2.8*	-0.10 *2.5*	-0.04 *0.7*	-0.10 *1.8*	-0.20 *2.8*	-0.06 *0.9*	-0.17 *2.0*	-0.05 *0.7*	-0.14 *1.2*	-0.13 *1.6*
R3	-0.10 *2.2*	0.00 *0.1*	-0.06 *1.0*	-0.07 *1.7*	-0.04 *0.9*	-0.10 *2.3*	-0.24 *3.5*	-0.10 *1.8*	-0.17 *2.2*	0.03 *0.4*	-0.06 *1.0*	-0.05 *0.7*
R4	-0.11 *1.9*	-0.12 *1.8*	-0.05 *1.0*	-0.04 *0.7*	-0.05 *0.9*	-0.16 *2.7*	-0.21 *2.0*	-0.14 *2.2*	-0.18 *2.0*	-0.24 *2.7*	-0.14 *1.6*	0.00 *0.1*
R5	-0.04 *0.6*	-0.08 *1.3*	-0.06 *1.0*	-0.09 *2.2*	-0.03 *0.8*	-0.17 *3.0*	-0.25 *3.3*	-0.12 *1.6*	-0.10 *1.4*	0.02 *0.2*	-0.10 *1.6*	-0.19 *2.3*
R6	-0.24 *2.7*	-0.23 *3.1*	-0.08 *1.7*	-0.12 *2.6*	0.03 *0.4*	-0.20 *2.7*	-0.23 *3.0*	0.02 *0.1*	-0.03 *0.3*	-0.02 *0.2*	0.00 *0.0*	-0.11 *1.2*
R7	0.03 *0.5*	0.00 *0.2*	0.04 *0.8*	0.05 *0.9*	0.06 *1.6*	0.06 *1.5*	-0.10 *1.6*	-0.02 *0.4*	0.15 *1.8*	0.21 *3.3*	0.06 *0.6*	0.25 *2.5*
R9	-0.14 *2.0*	-0.14 *1.9*	-0.11 *1.9*	-0.17 *2.8*	-0.02 *0.4*	-0.19 *3.1*	-0.24 *3.5*	-0.16 *2.7*	-0.12 *1.5*	-0.11 *1.6*	-0.13 *2.3*	-0.04 *0.5*
R10	-0.14 *2.3*	-0.22 *3.4*	-0.09 *2.1*	-0.02 *0.2*	0.00 *0.1*	-0.19 *2.4*	-0.17 *1.4*	0.02 *0.2*	-0.13 *1.6*	-0.06 *0.7*	-0.15 *1.3*	-0.24 *2.7*
R11	-0.08 *1.6*	-0.12 *2.2*	-0.07 *1.6*	-0.03 *0.5*	-0.02 *0.6*	0.03 *0.6*	-0.08 *1.3*	-0.02 *0.4*	-0.09 *1.3*	-0.08 *1.1*	0.03 *0.5*	0.05 *0.7*
Obs	589	479	581	538	662	528	260	344	291	240	213	220
R bar sq.	0.318	0.275	0.225	0.206	0.395	0.437	0.224	0.384	0.379	0.273	0.251	0.366
DW	1.96	1.90	1.81	1.87	1.94	1.95	2.03	1.85	1.86	1.85	1.88	1.88
Hetero	54.15**	54.88**	93.26**	85.08**	46.19**	239.9**	19.41	56.46**	37.24*	21.82	47.39**	23.99
Regional	10.85**	8.68**	5.39*	3.83	0.40	11.54**	16.02**	2.22	3.21	0.18	1.99	0.96
F(21,obs)	14.04**	9.62**	9.02**	7.63**	21.52**	20.47**	4.56**	11.19**	9.43**	5.27**	5.10**	7.08**

Table 6.6 Returns to individual characteristics in construction 1985 to 1995.

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Intercept	3.06 *14.7*	3.17 *21.5*	3.38 *23.3*	3.26 *28.0*	3.06 *15.9*	3.50 *20.6*	3.69 *20.2*	3.60 *26.9*	3.79 *21.1*	3.75 *20.3*	3.84 *25.4*
Exp	0.04 *3.4*	0.04 *4.5*	0.03 *3.5*	0.04 *5.2*	0.05 *4.5*	0.03 *2.6*	0.02 *1.4*	0.02 *2.3*	0.09 *0.8*	0.00 *0.1*	-0.01 *2.5*
$Exp^2 \times 100$	-0.06 *2.7*	-0.06 *4.0*	-0.05 *3.5*	-0.07 *4.9*	-0.08 *4.0*	-0.05 *2.3*	-0.04 *1.6*	-0.04 *2.4*	-0.03 *1.1*	-0.00 *0.0*	0.00 *0.5*
Part Time	-0.99 *1.8*	-0.59 *2.9*	0.00 *0.0*	0.00 *0.0*	-0.79 *5.1*	0.00 *0.0*	-0.49 *3.7*	-1.48 *4.5*	-1.46 *3.2*	-1.84 *4.3*	-1.27 *3.4*
Married	0.12 *1.3*	0.03 *0.6*	0.19 *2.7*	0.19 *2.8*	0.14 *2.0*	0.02 *0.4*	0.19 *2.7*	0.02 *0.3*	-0.06 *0.5*	-0.01 *0.2*	0.09 *1.0*
Non White	-0.19 *1.5*	-0.13 *0.9*	0.23 *2.5*	0.35 *3.0*	-0.23 *1.1*	-0.13 *1.2*	0.14 *1.0*	-0.26 *2.2*	0.04 *0.4*	-0.18 *1.0*	-0.19 *1.5*
Degree	0.56 *4.4*	0.72 *6.0*	0.46 *5.5*	0.47 *4.3*	0.53 *6.9*	0.82 *6.9*	0.47 *5.5*	0.88 *6.7*	0.52 *2.5*	0.59 *2.3*	0.54 *4.7*
Vocational	0.49 *4.7*	0.33 *4.3*	0.32 *3.4*	0.42 *4.5*	0.17 *1.8*	0.38 *3.8*	0.29 *2.6*	0.07 *0.6*	0.38 *4.3*	0.26 *2.2*	0.35 *2.7*
A'Level	0.39 *5.1*	0.41 *3.8*	0.20 *2.5*	0.24 *2.5*	0.24 *2.6*	0.25 *2.5*	0.17 *1.5*	0.17 *2.2*	-0.03 *0.2*	0.01 *0.1*	0.30 *2.5*
O'Level	0.21 *3.2*	0.17 *2.5*	0.13 *1.6*	0.23 *2.5*	0.13 *1.3*	0.06 *0.5*	0.08 *0.8*	-0.01 *0.2*	-0.01 *0.1*	-0.01 *0.1*	0.09 *0.9*
Apprentice	0.01 *0.1*	0.08 *1.5*	0.04 *0.6*	0.08 *1.0*	0.10 *1.0*	0.06 *0.5*	-0.01 *0.1*	0.16 *1.7*	0.02 *0.1*	-0.03 *0.3*	0.17 *1.7*
Other	0.16 *1.2*	0.39 *2.1*	0.21 *1.7*	0.13 *0.7*	0.18 *1.1*	0.53 *4.4*	-0.15 *1.1*	-0.03 *0.3*	0.17 *0.8*	0.10 *0.9*	-0.35 *1.4*
R1	-0.07 *0.6*	-0.15 *1.6*	-0.14 *1.5*	-0.46 *3.5*	-0.20 *1.5*	-0.31 *1.7*	-0.22 *1.9*	-0.03 *0.2*	-0.32 *2.3*	-0.02 *0.1*	0.00 *0.1*
R2	-0.20 *2.0*	-0.15 *1.7*	-0.23 *2.7*	-0.26 *2.2*	-0.29 *2.4*	-0.29 *2.5*	-0.15 *1.3*	-0.03 *0.4*	-0.54 *2.8*	0.13 *0.9*	-0.37 *2.9*
R3	-0.14 *1.3*	-0.17 *1.8*	-0.17 *2.2*	-0.25 *3.1*	-0.05 *0.4*	-0.26 *2.1*	-0.19 *1.7*	-0.26 *2.7*	-0.19 *1.1*	-0.08 *0.5*	-0.27 *1.3*
R4	-0.18 *1.6*	-0.15 *1.4*	-0.15 *2.0*	-0.03 *0.2*	-0.10 *0.9*	-0.39 *2.9*	-0.22 *1.9*	-0.23 *1.7*	-0.40 *1.7*	-0.15 *1.3*	-0.17 *1.8*
R5	0.13 *0.8*	-0.24 *2.8*	-0.24 *2.5*	-0.15 *1.2*	-0.23 *1.9*	-0.12 *0.8*	-0.16 *1.2*	0.06 *0.6*	-0.05 *0.3*	0.00 *0.0*	-0.29 *2.1*
R6	0.03 *0.2*	0.03 *0.2*	0.16 *0.6*	-0.06 *0.6*	-0.05 *0.5*	0.09 *0.4*	-0.38 *4.2*	0.07 *0.7*	0.23 *0.6*	0.03 *0.2*	-0.03 *0.2*
R7	-0.05 *0.4*	-0.03 *0.4*	0.05 *0.5*	0.02 *0.2*	0.23 *2.1*	-0.03 *0.3*	0.04 *0.5*	0.08 *0.7*	-0.03 *0.3*	0.13 *1.0*	-0.08 *0.9*
R9	-0.21 *2.0*	-0.11 *1.3*	-0.44 *4.3*	-0.11 *1.2*	-0.18 *1.7*	0.04 *0.3*	-0.03 *0.2*	-0.08 *1.0*	-0.17 *1.2*	-0.24 *1.5*	-0.28 *2.6*
R10	-0.04 *0.3*	0.00 *0.1*	-0.34 *3.1*	-0.27 *1.9*	-0.05 *0.3*	-0.05 *0.4*	-0.03 *0.3*	-0.21 *1.3*	-0.42 *2.7*	-0.06 *0.5*	0.13 *0.9*
R11	-0.02 *0.2*	-0.16 *2.1*	-0.14 *1.7*	-0.21 *2.4*	-0.11 *0.9*	-0.07 *0.4*	-0.27 *2.4*	0.09 *0.9*	-0.11 *1.1*	-0.05 *0.5*	-0.13 *1.2*
Obs	207	200	206	151	159	140	168	324	270	259	448
R bar sq	0.306	0.317	0.273	0.293	0.262	0.239	0.220	0.227	0.126	0.159	0.136
DW	2.08	2.27	1.96	2.03	2.05	1.96	2.21	1.89	2.11	1.87	2.02
Hetero	148.9**	87.62**	66.05**	35.03*	30.74	44.70**	40.38*	67.15**	127.8**	142.2**	245.6**
Regional	1.15	3.09	8.41**	6.31*	1.60	1.69	4.36*	0.69	3.48	0.10	3.48
F(21,obs)	5.32**	5.40**	4.84**	4.11**	3.67**	3.19**	3.24**	5.52**	2.85**	3.32**	4.36**

Table 6.7 Returns to individual characteristics in transport and communication 1973 to 1984.

	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Intercept	3.22 *40.7*	3.28 *36.4*	3.29 *37.2*	3.25 *42.0*	3.09 *48.4*	3.35 *36.5*	3.31 *29.7*	3.37 *29.1*	3.43 *27.4*	3.52 *31.4*	1.66 *10.2*	3.47 *18.1*
Exp	0.03 *6.1*	0.02 *3.9*	0.02 *4.3*	0.02 *4.8*	0.03 *6.8*	0.02 *3.5*	0.03 *4.6*	0.03 *4.1*	0.02 *2.4*	0.03 *3.4*	0.05 *4.1*	0.01 *0.9*
$Exp^2 \times 100$	-0.06 *6.3*	-0.04 *4.4*	-0.04 *4.9*	-0.05 *5.4*	-0.06 *6.7*	-0.04 *3.9*	-0.06 *4.9*	-0.06 *4.6*	-0.04 *2.5*	-0.05 *3.3*	-0.08 *4.2*	-0.02 *1.1*
Part Time	-0.84 *3.3*	-1.37 *8.5*	-1.29 *15*	-0.52 *1.6*	-0.69 *2.7*	-1.57 *4.5*	-0.98 *8.9*	-1.15 *8.4*	-0.84 *3.0*	-0.24 *0.6*	-0.91 *2.7*	-1.44 *2.3*
Married	0.06 *0.9*	0.09 *1.8*	0.06 *1.2*	0.07 *1.4*	0.17 *5.1*	0.07 *1.3*	0.04 *0.7*	0.04 *0.6*	0.10 *1.9*	-0.01 *0.2*	0.04 *0.5*	0.24 *2.9*
Non White	0.02 *0.3*	-0.09 *1.5*	-0.07 *1.6*	-0.02 *0.3*	-0.04 *0.9*	-0.00 *0.1*	-0.01 *0.1*	-0.01 *0.1*	-0.07 *1.0*	0.13 *1.3*	-0.05 *0.6*	0.33 *1.9*
Degree	0.62 *3.8*	0.60 *7.4*	0.41 *2.6*	0.36 *2.6*	0.56 *4.1*	0.38 *3.5*	0.59 *5.9*	0.34 *3.5*	0.53 *3.4*	0.54 *6.5*	0.79 *4.2*	0.58 *4.5*
Vocational	0.67 *6.0*	0.56 *5.8*	0.38 *4.5*	0.33 *3.6*	0.51 *6.7*	0.35 *4.4*	0.38 *4.1*	0.42 *4.2*	0.37 *3.1*	0.57 *9.4*	0.29 *3.1*	0.71 *4.1*
A'Level	0.29 *3.2*	0.30 *5.2*	0.25 *3.5*	0.20 *4.1*	0.22 *3.8*	0.23 *3.3*	0.23 *3.1*	0.15 *2.5*	0.42 *3.9*	0.27 *2.4*	0.26 *2.5*	0.20 *1.8*
O'Level	0.22 *4.7*	0.22 *4.2*	0.19 *4.2*	0.21 *5.0*	0.13 *3.4*	0.16 *3.7*	0.05 *0.9*	0.06 *1.1*	0.16 *3.3*	0.18 *3.3*	0.19 *2.9*	0.22 *2.2*
Apprentice	0.12 *2.4*	-0.05 *0.9*	0.03 *0.7*	0.06 *1.3*	0.03 *0.8*	0.02 *0.3*	0.02 *0.3*	0.06 *1.0*	0.01 *0.1*	0.07 *0.7*	0.05 *0.6*	0.07 *0.9*
Other	0.12 *2.7*	0.15 *2.1*	0.05 *0.9*	0.15 *2.9*	0.13 *2.6*	0.20 *2.6*	0.19 *2.5*	0.06 *0.8*	0.05 *0.6*	0.19 *2.4*	0.25 *2.5*	-0.03 *0.2*
R1	-0.11 *1.7*	-0.01 *0.2*	-0.14 *2.6*	-0.07 *1.2*	0.14 *2.5*	-0.06 *0.7*	-0.26 *2.8*	-0.04 *0.5*	-0.19 *2.0*	-0.11 *1.0*	-0.01 *0.1*	-0.07 *0.8*
R2	-0.15 *2.9*	-0.13 *2.3*	-0.08 *1.7*	-0.10 *1.7*	-0.16 *3.6*	-0.22 *4.4*	-0.08 *1.3*	-0.15 *2.1*	-0.17 *2.0*	-0.25 *2.7*	-0.11 *1.3*	-0.12 *1.1*
R3	-0.16 *3.3*	-0.15 *2.7*	-0.12 *3.3*	0.00 *0.1*	-0.11 *2.5*	-0.11 *2.5*	-0.13 *2.1*	-0.10 *1.6*	-0.16 *2.4*	-0.25 *3.3*	-0.04 *0.4*	-0.15 *1.6*
R4	-0.15 *2.8*	-0.16 *2.9*	-0.09 *1.5*	-0.11 *2.1*	-0.24 *4.1*	-0.18 *2.6*	-0.09 *1.2*	-0.07 *1.1*	-0.16 *1.8*	-0.33 *3.1*	-0.17 *1.6*	-0.27 *2.9*
R5	-0.10 *1.5*	-0.13 *2.2*	-0.04 *1.0*	-0.05 *1.0*	-0.12 *2.6*	-0.09 *1.6*	0.15 *1.6*	0.03 *0.4*	0.00 *0.1*	-0.32 *3.9*	-0.07 *0.8*	-0.16 *1.8*
R6	-0.12 *1.6*	-0.15 *1.4*	-0.03 *0.3*	-0.13 *1.8*	-0.27 *2.6*	-0.24 *3.7*	-0.20 *2.4*	-0.10 *1.0*	-0.11 *1.2*	-0.23 *2.7*	-0.03 *0.2*	-0.01 *0.2*
R7	-0.10 *2.1*	-0.01 *0.3*	0.02 *0.5*	0.08 *2.1*	-0.01 *0.4*	0.02 *0.5*	-0.03 *0.5*	0.06 *0.8*	0.07 *1.2*	-0.07 *1.0*	0.10 *1.2*	0.03 *0.3*
R9	-0.11 *1.6*	-0.1 *1.5*	-0.22 *4.1*	-0.09 *1.7*	-0.12 *2.5*	-0.16 *3.3*	-0.13 *2.3*	0.12 *1.2*	0.13 *0.8*	-0.25 *3.0*	0.01 *0.1*	-0.12 *0.9*
R10	-0.27 *3.4*	-0.1 *1.5*	-0.12 *1.9*	-0.08 *0.9*	-0.20 *3.2*	-0.15 *1.8*	-0.15 *2.1*	-0.06 *0.7*	-0.27 *2.2*	-0.05 *0.4*	-0.14 *1.5*	-0.41 *1.5*
R11	-0.15 *3.3*	-0.17 *3.5*	-0.03 *0.6*	-0.06 *1.5*	-0.16 *3.2*	-0.15 *2.7*	-0.11 *1.8*	-0.02 *0.3*	-0.06 *0.9*	-0.25 *2.8*	-0.16 *2.0*	-0.25 *2.9*
Obs	560	527	577	593	606	518	291	324	320	216	177	179
R bar sq.	0.321	0.335	0.261	0.200	0.332	0.370	0.347	0.265	0.309	0.369	0.301	0.401
DW	1.78	2.09	2.02	1.89	1.89	1.91	1.97	2.02	1.85	1.92	1.88	1.85
Hetero	154.2**	48.19**	57.12**	138.9**	154.2**	135.1**	37.12*	26.27	299.4**	37.21*	81.26**	189.5**
Regional	15.69**	9.12**	8.72**	4.30*	24.73**	16.40**	6.23*	0.46	2.78	12.56**	1.10	4.28*
F(21,obs)	13.57**	13.63**	10.71**	8.05**	15.30**	15.44**	8.35**	6.55**	7.79**	6.98**	5.75**	6.68**

Table 6.8 Returns to individual characteristics in transport and communication 1985 to 1995.

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Intercept	3.47 *18.0*	3.13 *25.7*	3.49 *25.3*	3.23 *17.6*	3.61 *26.4*	3.20 *19.7*	3.47 *25.2*	4.00 *25.6*	3.53 *14.3*	3.34 *17.4*	3.47 *19.4*
Exp	0.03 *3.3*	0.05 *6.7*	0.02 *2.8*	0.05 *3.6*	0.03 *3.4*	0.05 *3.8*	0.03 *2.7*	-0.01 *1.5*	0.03 *2.0*	0.04 *2.9*	0.03 *2.7*
$Exp^2 \times 100$	-0.06 *2.9*	-0.09 *6.8*	-0.04 *2.2*	-0.07 *2.7*	-0.07 *3.8*	-0.07 *2.9*	-0.04 *2.3*	0.00 *0.4*	-0.05 *1.9*	-0.07 *2.8*	-0.06 *2.8*
Part Time	-0.93 *1.9*	-0.83 *6.3*	-1.36 *6.2*	0.19 *1.8*	-1.36 *5.5*	-1.27 *2.2*	-1.41 *9.3*	-0.86 *3.7*	-1.19 *6.0*	-0.57 *1.9*	-1.32 *7.1*
Married	0.01 *0.1*	0.05 *1.1*	0.05 *0.8*	-0.06 *0.9*	0.08 *1.3*	0.16 *2.3*	-0.01 *0.2*	0.11 *1.4*	-0.07 *0.6*	-0.07 *0.8*	0.10 *1.3*
Non White	-0.05 *0.4*	-0.19 *2.8*	-0.16 *2.1*	-0.50 *3.5*	0.05 *0.3*	-0.19 *1.3*	-0.06 *0.6*	-0.03 *0.2*	-0.03 *0.3*	-0.24 *1.6*	-0.21 *1.4*
Degree	0.47 *4.1*	0.56 *5.4*	0.74 *3.9*	0.66 *7.4*	0.55 *5.1*	0.87 *8.0*	0.96 *11.2*	0.56 *2.3*	0.76 *4.3*	0.85 *5.3*	0.73 *5.7*
Vocational	0.37 *3.6*	0.51 *5.8*	0.45 *4.9*	0.50 *3.9*	0.32 *2.8*	0.56 *4.8*	0.59 *5.6*	0.15 *1.2*	0.39 *2.4*	0.93 *5.5*	0.31 *3.0*
A'Level	0.22 *2.2*	0.27 *3.2*	0.36 *4.7*	0.56 *4.3*	0.16 *1.8*	0.42 *3.8*	0.34 *3.3*	0.07 *0.7*	0.12 *0.8*	0.26 *2.2*	0.12 *1.0*
O'Level	0.12 *1.8*	0.28 *4.1*	0.19 *2.6*	0.41 *3.7*	0.21 *2.8*	0.39 *3.9*	0.42 *5.0*	-0.02 *0.3*	0.24 *2.1*	0.16 *1.6*	0.06 *0.7*
Apprentice	-0.16 *1.1*	0.07 *0.7*	-0.03 *0.4*	0.11 *1.0*	0.03 *0.4*	-0.65 *1.9*	0.25 *2.0*	0.05 *0.4*	0.06 *0.3*	0.09 *0.3*	-0.49 *3.1*
Other	-0.04 *0.3*	0.21 *2.1*	0.11 *1.6*	0.39 *4.1*	-0.02 *0.3*	0.22 *2.4*	0.10 *1.1*	0.08 *0.7*	0.16 *1.5*	0.35 *2.4*	0.08 *0.9*
R1	-0.22 *1.7*	-0.22 *2.4*	-0.14 *1.2*	-0.48 *3.1*	-0.18 *1.5*	-0.24 *1.4*	-0.25 *2.9*	-0.06 *0.5*	-0.12 *0.6*	-0.16 *1.0*	-0.32 *1.7*
R2	-0.22 *2.0*	-0.07 *0.6*	-0.11 *1.4*	-0.25 *2.1*	-0.36 *3.0*	-0.25 *3.1*	-0.21 *2.4*	-0.39 *2.7*	-0.13 *1.0*	-0.24 *1.9*	-0.05 *0.4*
R3	-0.18 *1.7*	-0.24 *2.8*	-0.24 *3.0*	-0.15 *1.3*	-0.08 *0.7*	-0.34 *4.0*	-0.26 *2.2*	-0.32 *2.5*	-0.16 *1.0*	-0.08 *0.6*	-0.12 *1.1*
R4	-0.04 *0.4*	-0.22 *3.4*	-0.12 *1.0*	-0.15 *1.2*	-0.23 *2.1*	-0.27 *1.6*	-0.17 *1.7*	-0.29 *1.5*	-0.18 *1.1*	-0.62 *2.8*	-0.17 *1.1*
R5	-0.25 *2.0*	-0.16 *2.1*	-0.18 *1.5*	-0.30 *3.7*	-0.26 *2.4*	-0.20 *1.9*	0.07 *0.7*	-0.12 *1.0*	-0.11 *0.7*	-0.30 *1.9*	-0.33 *2.7*
R6	0.02 *0.2*	0.03 *0.3*	-0.13 *1.4*	-0.04 *0.5*	0.03 *0.2*	-0.07 *0.8*	-0.17 *1.8*	0.02 *0.2*	-0.24 *0.9*	-0.23 *1.2*	-0.09 *0.9*
R7	-0.02 *0.2*	0.00 *0.1*	-0.02 *0.2*	0.13 *1.1*	-0.03 *0.4*	-0.16 *1.9*	-0.04 *0.6*	-0.03 *0.2*	0.19 *1.6*	0.09 *0.9*	-0.04 *0.3*
R9	-0.16 *1.2*	-0.13 *1.5*	-0.17 *2.4*	-0.20 *2.1*	-0.26 *2.9*	-0.35 *1.8*	-0.16 *1.0*	-0.35 *2.0*	0.00 *0.1*	-0.32 *1.5*	-0.13 *1.2*
R10	-0.24 *1.4*	-0.38 *3.1*	-0.32 *2.5*	-0.09 *0.6*	-0.50 *1.5*	-0.36 *3.0*	-0.06 *0.5*	-0.15 *1.2*	-0.15 *0.7*	-0.75 *2.2*	-0.24 *1.6*
R11	-0.18 *1.5*	-0.13 *1.7*	-0.02 *0.3*	-0.15 *1.4*	-0.31 *3.0*	-0.24 *2.2*	-0.03 *0.3*	-0.24 *1.7*	-0.06 *0.5*	0.14 *1.1*	-0.38 *3.0*
Obs	237	196	204	142	145	166	162	290	219	256	305
R bar sq	0.150	0.421	0.376	0.337	0.489	0.459	0.449	0.149	0.183	0.251	0.317
DW	1.85	1.86	2.05	1.84	2.01	1.96	2.24	2.06	2.09	2.04	1.98
Hetero	83.05**	28.58	48.68**	26.86	48.86**	114.7**	35.84*	71.79**	43.95**	85.90**	60.20**
Regional	4.19*	8.78**	6.83**	4.91*	9.65**	9.50**	4.08*	4.28*	1.11	6.92**	6.28*
F(21,obs)	2.98**	7.75**	6.83**	4.41**	7.58**	7.68**	7.27**	3.41**	3.32**	5.07**	7.71**

We now turn to consider the impact of changes in the relative supply and demand for different workers' characteristics. Previous evidence for the UK has found that the demand for certain characteristics, namely skills, rose at a faster pace than the corresponding supply (Schmitt, 1995; Machin, 1996[a,b]; Gosling, Machin and Meghir, 1996). For comparisons based on two groups at a point in time (in this instance the educated and uneducated), the relative supply of group 1 compared to group 2, is the ratio of the number of the educated to uneducated $E_1 \div E_2$. Relative supply changes over time t_0 to t_1 can then be measured by : $\Delta S_{12} = \left\{ \left[\log\left(\frac{E_1}{E_2}\right)_{t_0} - \log\left(\frac{E_1}{E_2}\right)_{t_1} \right] \div (t_0 - t_1) \right\} \times 100$. If we consider changes in wage premiums over time it is then possible to deduce how demand has altered.

Table 6.9 Percentage changes in relative supply and wages

		1975-1980		1980-1985		1985-1990		1990-1994	
E1/E2		ΔS_{12}	ΔWage	ΔS_{12}	ΔWage	ΔS_{12}	ΔWage	ΔS_{12}	ΔWage
Degree/No Qual.	*Manu.*	17	-2.3	15	3	7	3	-2	0.4
	Omanu.	19	2.3	24	0.01	2	8.1	10	-0.7
	Const.	33	3.1	1	1.5	5	3.7	-2	-4.9
	Trans.	15	-1.5	44	2.6	5	5.3	5	-0.3
Higher Vocational/ No Qual.	*Manu.*	20	-1.5	11	-0.7	11	2.8	-0.3	-2
	Omanu.	18	-4.5	15	2.5	5	3.9	13	-0.04
	Const.	26	-1.8	6	5.7	8	-0.6	-0.2	-2
	Trans.	11	0.7	13	-0.9	4	-2.3	7	7.3
A Level/No Qual	*Manu.*	11	-0.8	11	-0.1	11	1.2	-1.2	0.01
	Omanu.	8	-0.3	9	1.1	8	4.1	9	0.3
	Const.	13	-2.7	3	5.6				
	Trans.	21	-1.9	10	1.4	5	2.9	0.9	-3.2

The figures for the changing returns (ΔWage) are calculated from Tables 6.1 to 6.8 and are based on premiums which are significant at the 5 per cent or 1 per cent level.

Changes in wage premiums on education over time can be given as $\Delta \text{Wage} = \left[\left(\frac{\mu_{t_0} - \mu_{t_1}}{t_0 - t_1}\right) \times 100\right]$, where μ is the return to education (Chapter Four, equation 4.3). The results presented above in Table 6.9 show that relative supply rose in each industry for the top three educational groups, with the exception of : Manufacturing across each educational group from 1990 to 1994, and the Construction industry for the top two educational bands from 1990 to 1994. Clearly, an increase in the relative supply of educated workers has occurred in each of the four industries, shown by the fact that ΔS_{12} is positive over the period 1975-1980, 1980-1985 and 1985-1990, which is consistent with what has happened at the aggregate economy level (Schmitt, 1995; Machin, 1996[a], Gosling, Machin and Meghir, 1996; and Machin, 1998). Such relative supply shifts should depress the returns to education. However this did not occur, especially for degree and A level holders over the period 1980 to 1990. Again this is consistent with previous UK evidence. For example Machin (1998) found that over the period 1980 to 1990, changes in the relative wage were positive for degree holders relative to those with no qualifications at 1.65 (Machin, 1998, Table 3). The same can be seen at the industry level where for degree holders the change in wage premium was positive - between 0.01 and 8.1 points. This implies that the demand for education increased over the period faster than the corresponding supply changes, consequently causing rising wage premiums.

Whilst prior to 1990 relative supply changes were positive, interestingly, the period 1990 to 1994 experienced a break in the trend. In certain industries, namely Manufacturing and Construction, the relative supply change became negative[1]. A contraction in the relative supply of education should raise the relative wage - in Manufacturing the supply of degree and A level holders relative to the no qualification group fell at a time of rising relative wages - suggesting that either supply outweighed falling demand shifts, or demand and supply moved in opposite directions. However, in the Construction industry for degree holders relative to the no qualification group relative supply fell as did the relative wage. This implies that although the supply change should raise the relative wage a larger negative demand shock actually meant relative wages fell. The same phenomenon occurred in Manufacturing and Construction for higher vocational education holders relative to the no qualification group.

The changing patterns in relative supply and wage premiums are consistent with what others have found at the economy wide level - in particular for the period 1980 to 1990 where in each industry it appears demand outweighed supply changes.

[1] The fall in relative supply of each educational group over the period 1990 to 1994 is inconsistent with evidence from the Labour Force Survey, where the relative supply increased from 1991 to 1994 for each education group of employed males (data taken from the web site http://cep.lse.ac.uk/datalib/training/uk/table3m.html table 3m). However, it should be noted that the LFS data is describing UK figures not industry level trends. This may explain why for instance in Manufacturing the number with a Degree relative to no qualifications fell by 2 per cent, yet rose by 10 per cent in Other Manufacturing. Moreover, checks of the General Household Survey at the aggregate level were in line with Machin (1998) in that relative supply of degree holders increased overall. Also, for each education group the relative fall is small - 0.3 per cent in Manufacturing for higher vocational qualifications - in comparison to the increases witnessed in other industries - 13 per cent in Other Manufacturing. Interestingly, for both the top two education groups the fall in relative supply occurs in the same industries, Manufacturing and Construction.

6.3 Model performance, variable signs and linear restrictions

Firstly, in sub-section 6.3.1, the influence of model performance upon earnings dispersion is investigated, in particular within-group earnings dispersion. Sub-section 6.3.2 looks at the returns in Tables 6.1 to 6.8 considering any anomalies with the empirical results in comparison to economic theory. Sub-section 6.3.3 looks at the impact of regions upon between-group earnings dispersion. The final sub-section 6.3.4 looks to see what influence the variation in hours worked per week may influence the trend in earnings dispersion.

6.3.1 Model performance and within-group earnings dispersion

The empirical model used to disaggregate earnings dispersion into between-group and within-group effects is based upon employing earnings functions (as discussed in Chapter Four). It is well known that the fit of such a function is very rarely above 50 per cent, that is, an $\overline{R}^2$ of 0.5, and this in turn influences the standard deviation. The following considers why this is so. The earnings function estimated in the first step, Chapter Four, equation 4.4, has a model fit given as :

$$\overline{R}^2 = 1 - \frac{\sum \hat{\varepsilon}_i^2 \div (N-k)}{\sum w_i^{\,2} \div (N-1)} = 1 - \frac{\hat{\sigma}_\varepsilon^2}{\sigma_w^2} \qquad \textbf{(6.1)}$$

where $\sum w_i^2 = \sum \left(\omega_i - \overline{\omega}\right)^2$, N is the number of observations and k the number of parameters. The residual variance is $\hat{\sigma}_\varepsilon^2$, an unbiased estimate of the true variance σ_ε^2, and σ_w^2 is the sample variance of ω. The measure of within-groups earnings dispersion used in the analysis is the standard deviation of the residual $\hat{\sigma}_\varepsilon$, thus there is a direct relationship between the fit of the model and the measure of earnings dispersion, since

$$\frac{\partial \overline{R}^2}{\partial \hat{\sigma}_\varepsilon^2} = -\frac{1}{\sigma_w^2} \langle 0 \qquad \textbf{(6.2)}$$

Consequently a low $\overline{R}^2$ implies a higher standard deviation of the residual. In terms of the analysis given here, this means that in years where differences in workers' characteristics are less able to explain earnings, it should be expected that within-group dispersion will be higher.

Figure 6.5 A cubic trend of Adjusted R - squared.

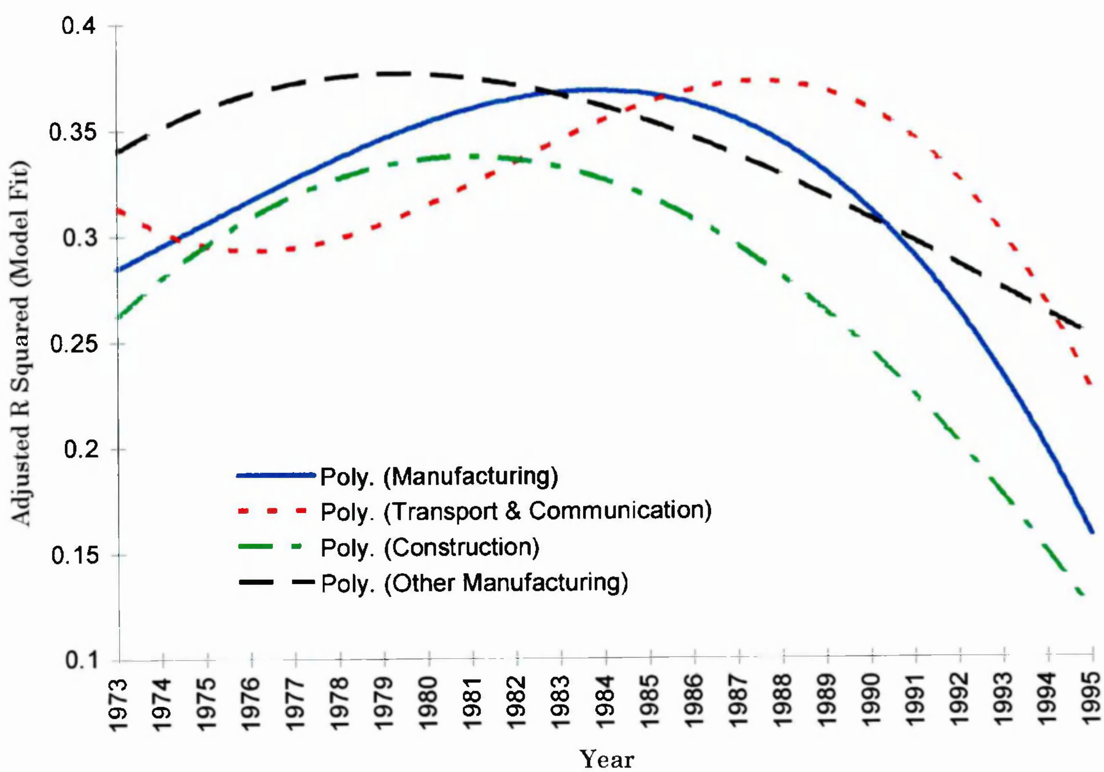


Figure 6.5, above, shows the cubic trend of $\overline{R}^2$ (shown in the fifth row from the bottom in each of Tables 6.1 to 6.8), where in each industry it has declined over the 1980s, although

not until the late 1980s in Transport and Communication. This is consistent with rising within-group dispersion, which is what is seen in Figures 6.1 to 6.4.

6.3.2 Empirical anomalies

Looking at the returns to personal and educational characteristics in Tables 6.1 to 6.8, the model appears to perform to theoretical expectations. In particular, the premium associated with educational qualifications declines monotonically across Degrees to O' Levels in almost all instances. Moreover, the return to the top three educational groups is nearly always statistically significant at the 5 per cent level. Over time the return to educational qualifications fluctuates, as do the returns to personal characteristics. However, the coefficients are correctly signed for the most part. In particular, higher experienced individuals earn more, part-time employees earn less, married workers earn more and education yields a positive return (Tables 6.1 to 6.8).

Contrary to theoretical expectations non-whites actually earned more in Construction in 1988 at 0.35 log points (Table 6.6). The same is also true in 1984 for Transport and Communication (Table 6.7), where the non-white indicator actually becomes positive at 0.33 log points. It is possible that the non-white dummy variable is correlated with another variable in the regression. However, just regressing earnings on a constant and a colour dummy, excluding all other variables, gives a positive and significant impact on earnings in both industries, as shown below in Table 6.10. The positive impact in the two industries should reduce between-group earnings dispersion, yet in Construction it rose slightly in 1988 (Figure 6.3) and the same is true for Transport and Communication in 1984 (Figure 6.4).

Table 6.10 The return to non-whites in Construction in 1988, and Transport and Communication in 1984

Construction				**Transport and communication**			
Intercept		**Non-White**		**Intercept**		**Non-White**	
3.8848	*(120)*	0.3547	*(1.99)*	3.7826	*(102)*	0.2492	*(1.67)*

This suggests that other factors other than colour influenced earnings to a greater extent in those years. Notably in 1984 in Transport and Communication the sharp increase in between-group earnings dispersion can be accounted for by a 4.2 log point increase in the return to vocational education (Table 6.7, 1983 to 1984) and an increase in the differential between full-time and part-time employees, with the return to part-time employees falling from -0.91 to -1.44 log points (Table 6.7).

6.3.3 Linear restrictions

Each of the Table's 6.1 to 6.8 reports two tests based upon linear restrictions. The first one, in the final row of each table tests the joint significance of each variable. That is, from Chapter Four equation 4.4, a test of the null hypothesis :

$$H_0 \text{ Parameters are jointly insignificant } \delta=0$$

$$H_1 \text{ Otherwise } \delta\neq 0$$

The test statistic is based upon an $F(n_1, n_2)$ test, distributed with 21 parameters (see Chapter Four, equation 4.3) in δ and the n_2 observations. This yields a critical value of $F(21,\infty)$~2.36 at the 1 per cent level. In all instances the null hypothesis can be rejected, which suggests that the coefficients estimated from the earnings function are jointly significant.

As well as controlling for human capital and personal characteristics in the first stage of the empirical procedure, the influence of regional pay variations is controlled for by regional indicators. A further hypothesis tested is whether the ten regional indicators (Chapter Five) are jointly significant. From the earnings function used in the first step (Chapter Four, equation 4.3),

$$lnW_i = \omega_i = \lambda + \beta Exp_i + \gamma Exp_i^2 + \sum_{q=1}^{3} \theta_q D_{iq} + \sum_{g=1}^{6} \mu_g Ed_{ig} + \sum_{h=1}^{10} \eta_h \, Region_{ih} + \varepsilon_i \quad \textbf{(6.3)}$$

This amounts to a test of whether the regional dummies are insignificant in the earnings function against the alternative. Thus for equation 6.3 :

$$H_0 \text{ Regional indicators are insignificant } \sum_{h=1}^{10} \eta_h = 0$$

$$H_1 \text{ Otherwise } \sum_{h=1}^{10} \eta_h \neq 0$$

This is tested using a Lagrange Multiplier test, giving a test statistic χ^2~(1) with a critical value of 6.63 at the 1 per cent level of significance and 3.84 at the 5 per cent. The results are shown in the penultimate row in Tables 6.1 to 6.8. Clearly, the two industries where regional indicators have the greatest impact on earnings are Manufacturing, and Transport and Communication. In these industries in 19 out of 23 cases, the null hypothesis can be rejected at the 5 per cent level. In Other Manufacturing this falls to 16 out of 23 at the 5 per cent level, and in Construction the null hypothesis could not be rejected in less than half the years (8/23).

Having found a significant role for regional indicators from a joint test, the following considers the possible impact upon between-group earnings dispersion of individual regions.

Table 6.11 Regions with the largest impact upon earnings, identified by year

	R1	R2	R3	R4	R5	R6	R9	R10	R11
Manufacturing	*1974* *1984*	*1973* *1975* *1977* *1981* *1985* *1987* *1990* *1992* *1993*	*1991*	*1982* *1983*		*1976* *1979*		*1978* *1980* *1986* *1988* *1989*	*1994* *1995*
Other Manufacturing	*1973* *1980*	*1992* *1993*	*1981*	*1975*	*1979*	*1983*	*1986* *1989*	*1977* *1978* *1984* *1985* *1987* *1990* *1994* *1995*	*1988* *1991*
Construction	*1979* *1988*	*1975* *1989* *1993* *1995*	*1992*	*1981* *1982* *1983* *1990*	*1986*	*1973* *1974* *1978* *1991*	*1976* *1980* *1985*	*1984* *1987*	
Transport and Communication	*1979* *1988*	*1980* *1989* *1992*	*1991*	*1982* *1983* *1984*	*1985*	*1976* *1977* *1978*	*1975*	*1973* *1981* *1986* *1987* *1990* *1994*	*1974* *1995*

Those regions identified are significant at the 5 per cent level.
Details based upon information from Tables 6.1 to 6.8.

Greater London (region R7) is excluded from Table 6.11 because in no year or industry did it have the lowest coefficient (at 5 per cent significance).

Figure 6.6 The number of times a region has largest impact upon earnings

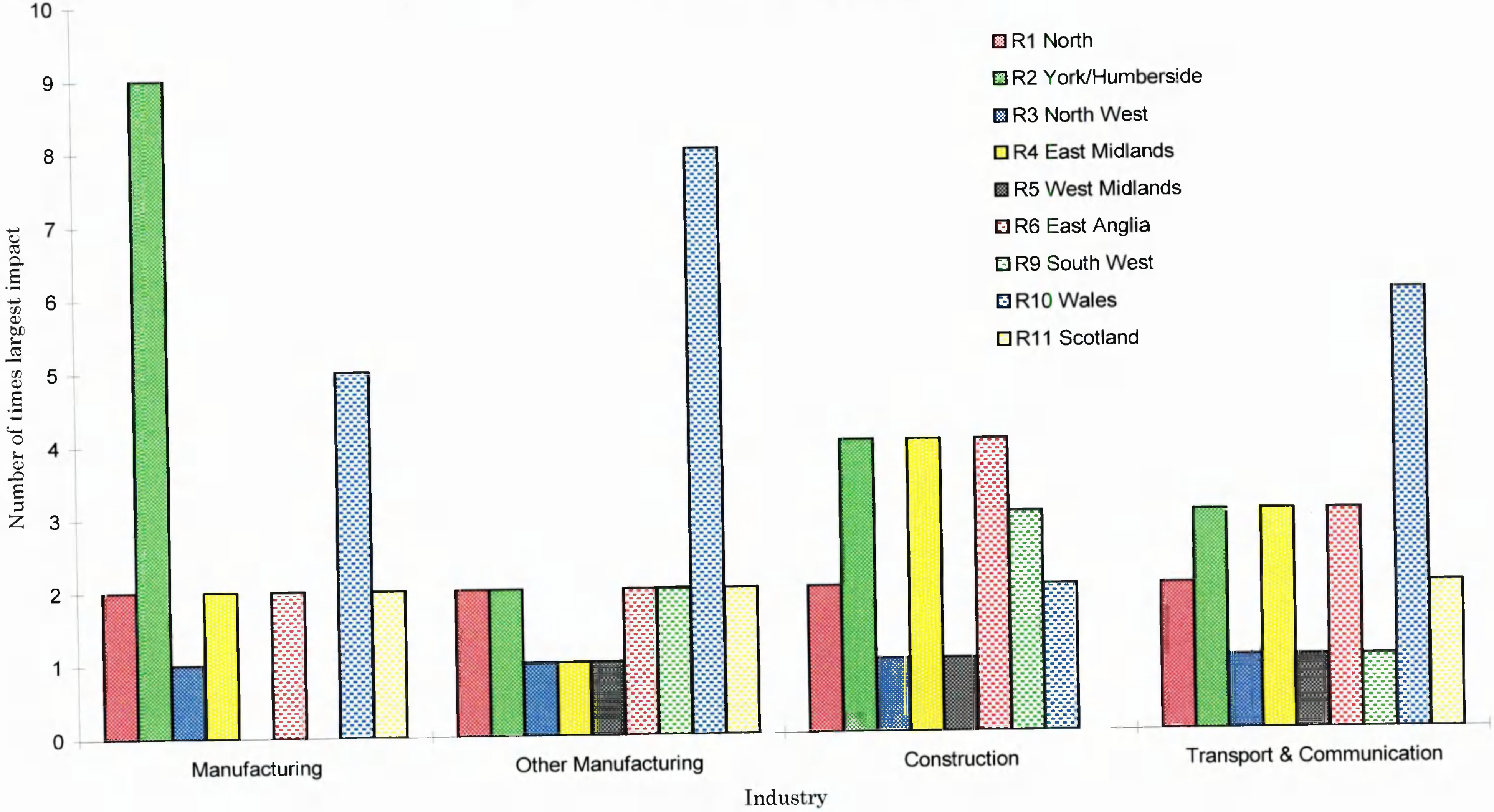
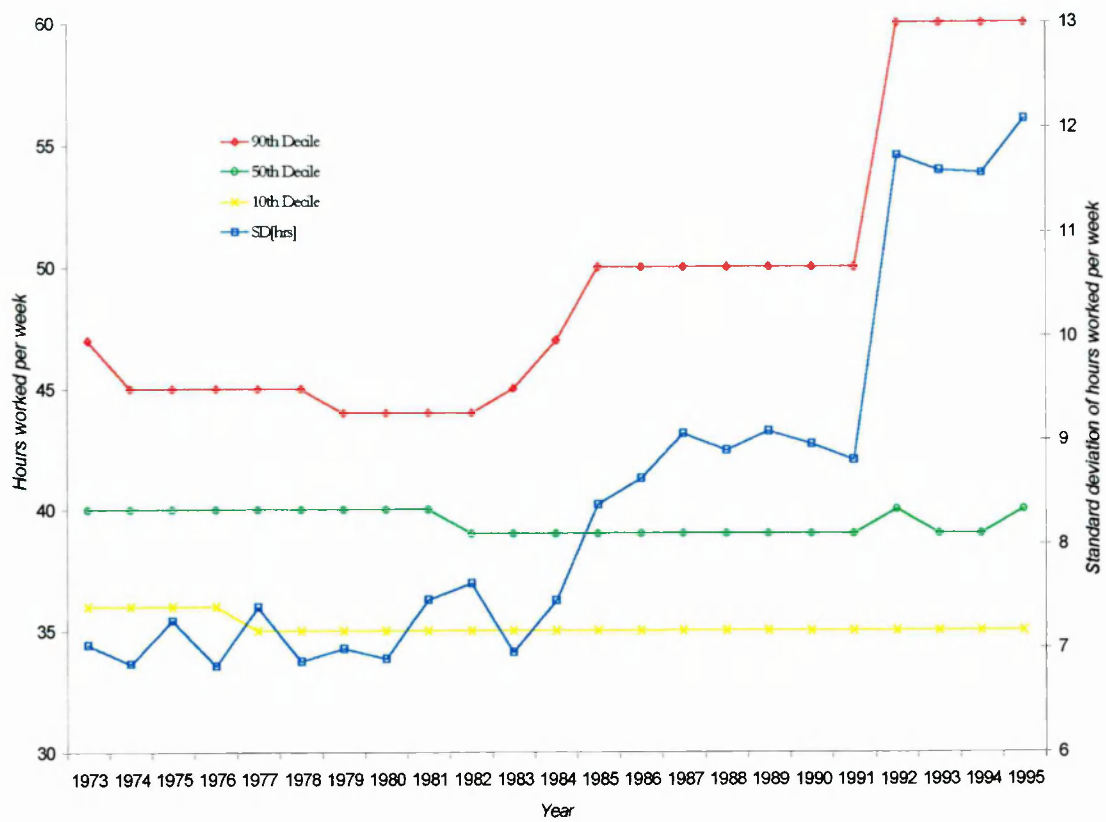


Table 6.11, above, identifies those regions, and the year in which the region has a significant impact upon earnings determination and was larger than in any other region. Figure 6.6 plots the number of times a region has the largest impact upon earnings. Clearly, in each industry, with the exception of Construction, Wales appears to be one of the worst regions and the one most likely to have the highest between-group regional inequality with reference to the South East. More significant is the fact that much of the impact of Wales' poor regional performance in terms of having the largest impact upon earnings has occurred in the late 1980s and early 1990s, as is apparent from Table 6.11. In Manufacturing the worst region is York and Humberside, where in 9 years out of 23 it has the greatest impact upon earnings. For Construction industry the three regions which equally fair the worst are York and Humberside, the East Midlands and East Anglia.

6.3.4 The role of hours worked over time

In chapter Five, the discontinuity in the measure of hours per week was discussed. Following from this discussion, the only indicator of the length of the working week is given by a part-time dummy indicator. Consequently, the results given so far have not included the number of hours worked per week in the analysis. It is possible that changes in the length of the working week could have an impact upon the trend in earnings dispersion that is not captured by the part-time dummy. Figure 6.7, below, shows a plot of the distribution of hours worked per week for Great Britain over the period 1973 to 1995. Clearly, the standard deviation of hours worked has increased over time and this is especially so during the 1990s. Moreover, it is clear that the sharp rise in the standard deviation is driven by people working longer rather than shorter hours as shown by the increase amongst those in the 90th decile of hours of work.

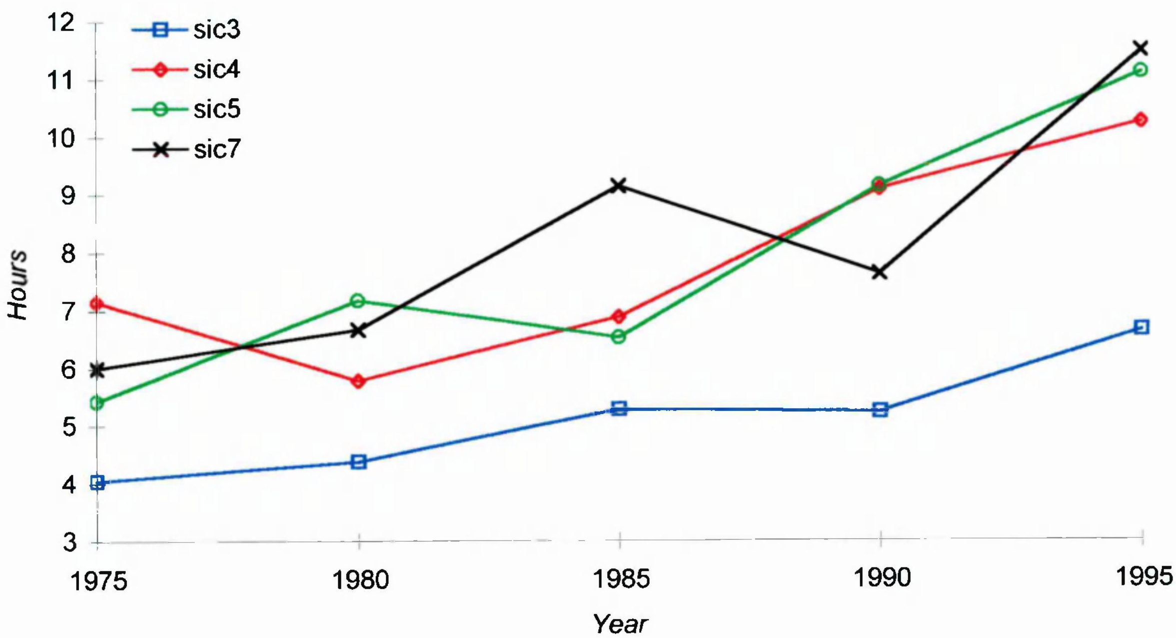
Figure 6.7 Distribution of hours worked per week in Great Britain 1973-1995



The issue we need to consider therefore is whether the same pattern is true for each industry and that the sharp rise in standard deviation of hours post 1990 coincides with the large rise in within-group earnings dispersion. Figure 6.8, below, considers the standard deviation in hours worked per week in each of the four industries over time. Again it is noticeable that the standard deviation has risen in each industry after 1990.

To address the issue of whether the variation in hours worked over time may have influenced the trend in earnings dispersion a set of banded hours dummies were entered into the regression of equation 6.3 (reproduced from Chapter Four, equation 4.3). The data for hours worked is inconsistent over time as a continuous variable, consequently banded dummies are used where it is hoped that they will pick up any variation over time. Hence

Figure 6.8 Standard deviation of hours per week by industry 1975 to 1995



$$\omega_i = \lambda + \beta \mathrm{Exp}_i + \gamma \mathrm{Exp}_i^2 + \sum_{q=1}^{2} \theta_q D_{iq} + \sum_{z=1}^{B} \pi_z \mathrm{Hours}_{iz} + \sum_{g=1}^{6} \mu_g \mathrm{Ed}_{ig} + \sum_{h=1}^{10} \eta_h \mathrm{Region}_{ih} + \varepsilon_i$$

(6.3′)

where equation 6.3′ is the same as 6.3, with the exception that the vector **D** now does not contain a part-time dummy only marriage and colour indicators. Equation 6.3′ is augmented with a vector of banded hour dummy variables given as **Hours**. For each of the four industries it was only possible to construct three bands consistently over five periods of time. These are a dummy for less than 30 hours, a dummy for between 30 and 50 hours, and a dummy for greater than 50 hours per week. The reference category was the less than 30 hours per week given that we are interested in the impact of changing hours at the upper end of the distribution (so B=2 in equation 6.3′).

Figure 6.9 Manufacturing SIC3

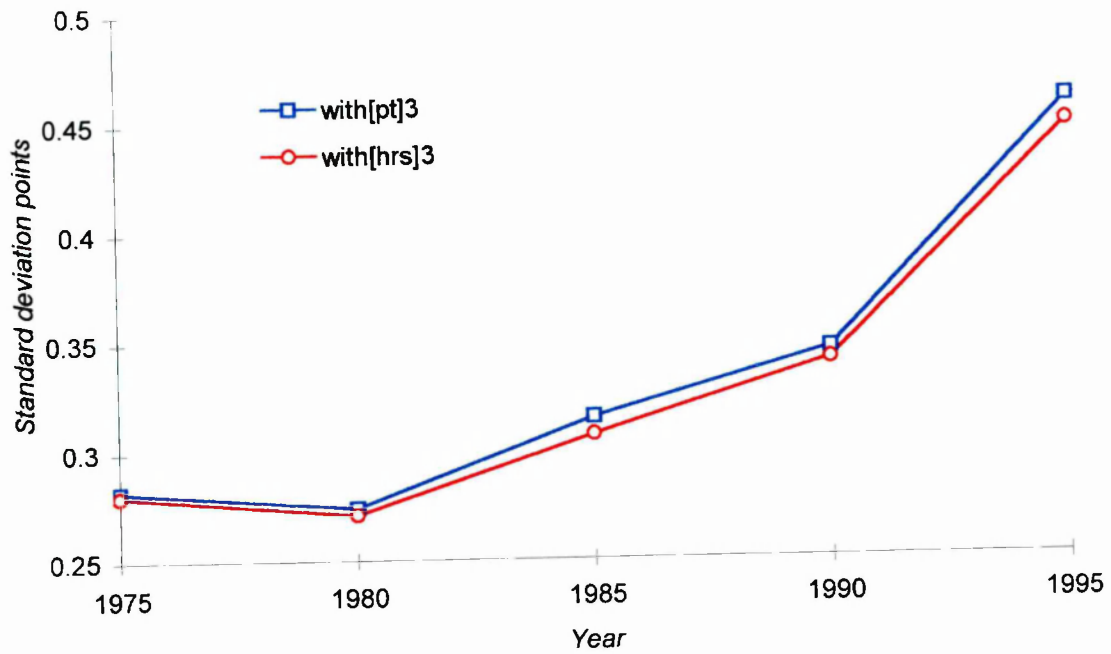


Figure 6.10 Other Manufacturing SIC4

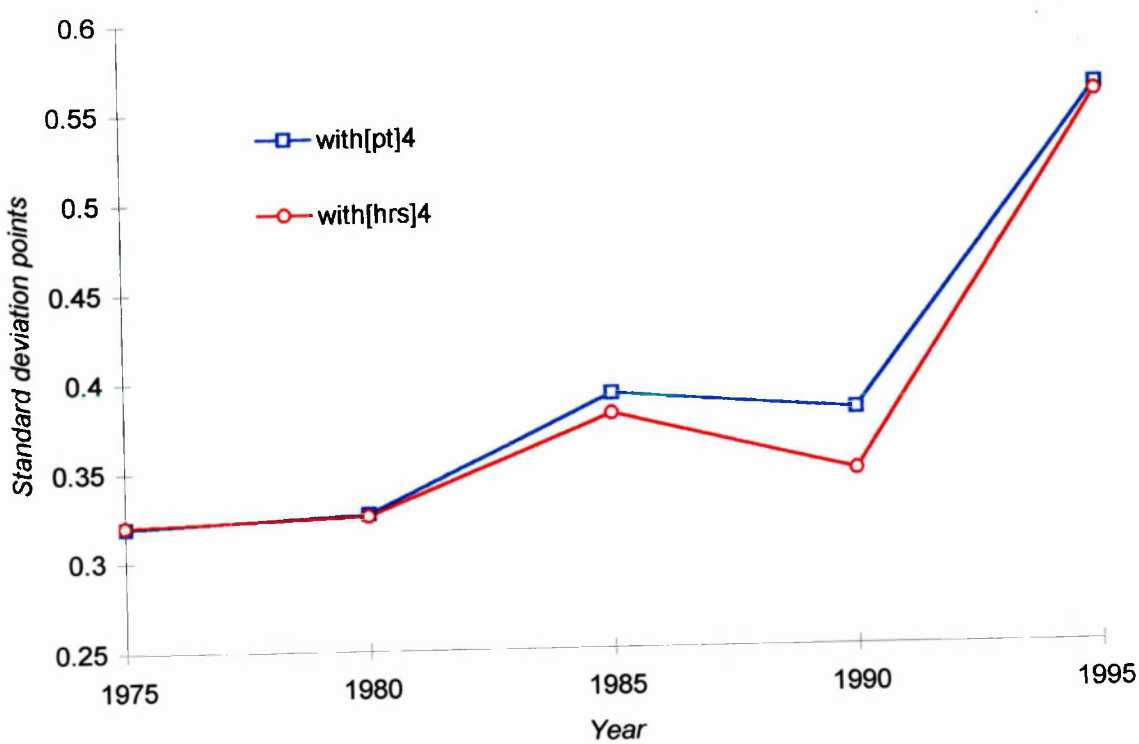


Figure 6.11 Construction SIC5

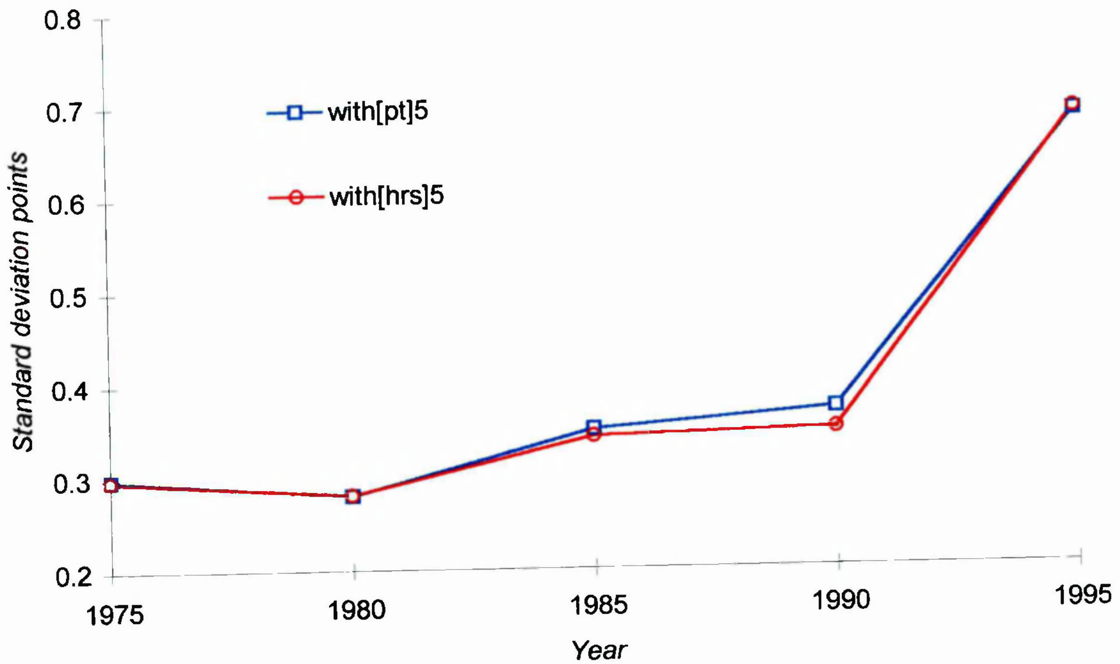
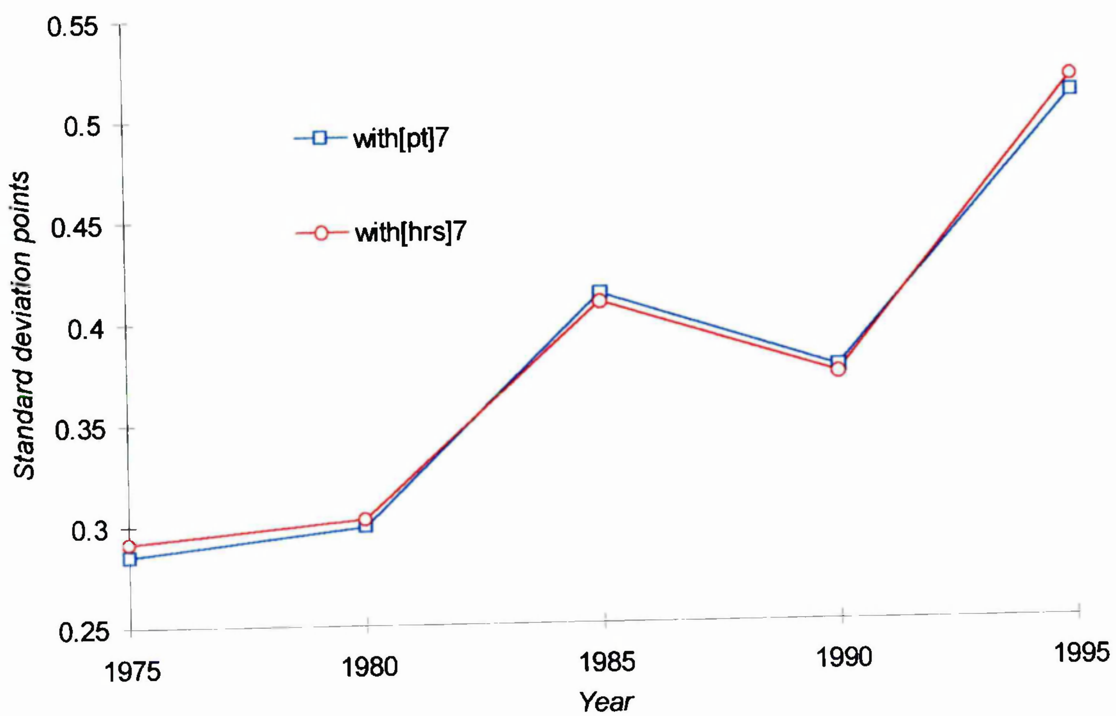


Figure 6.12 Transport and Communication SIC7



If the variation in hours per week is influencing the trend in earnings dispersion then the inclusion of the upper band of greater than 50 hours should pick this up. The results for each industry are shown above in figures 6.9 to 6.12. Clearly, from each of the figures above the trend in within-group earnings dispersion (the standard deviation of the residual from equation 6.3′, defined in Chapter Four equation 4.6) remains the same regardless of whether a simple part-time dummy is used (with[pt]) or the banded hour dummies (with[hrs]). Tables 6.12 to 6.15, below, show the coefficients and significance[1] associated with each hours band.

Table 6.12 Manufacturing

	1975	1980	1985	1990	1995
30 to 50 hours	0.099	0.851	1.078	0.654	0.672
	(3.76)	*(3.77)*	*(5.55)*	*(1.47)*	*(2.51)*
Greater than 50 hours	1.118	1.095	*1.372*	0.907	0.989
	(4.08)	*(4.59)*	(6.48)	*(2.02)*	*(3.59)*
R bar squared	0.286	0.324	0.415	0.354	0.211
Observations	1201	652	430	324	517

Table 6.13 Other Manufacturing

	1975	1980	1985	1990	1995
30 to 50 hours	0.489	0.924	0.828	1.780	1.452
	(3.91)	*(5.24)*	*(2.33)*	*(12.08)*	*(7.43)*
Greater than 50 hours	0.694	1.190	0.992	1.998	1.747
	(4.70)	*(6.05)*	*(2.73)*	*(12.56)*	*(8.38)*
R bar squared	0.365	0.413	0239	0.387	0.357
Observations	656	382	279	183	494

[1] T ratios are shown in parenthesis based upon heteroscedastic consistent standard errors, see section 6.4.2.

Table 6.14 Construction

	1975	1980	1985	1990	1995
30 to 50 hours	0.708	0.665	0.920	0.301	0.999
	(2.04)	*(3.48)*	*(1.96)*	*(3.5)*	*(2.88)*
Greater than 50 hours	0.823	0.829	1.146	0.379	1.171
	(2.35)	*(4.11)*	*(2.39)*	*(3.17)*	*(3.30)*
R bar squared	0.229	0.394	0.319	0.332	0.145
Observations	581	344	207	140	448

Table 6.15 Transport and Communication

	1975	1980	1985	1990	1995
30 to 50 hours	0.714	0.603	0.902	1.099	1.103
	(3.14)	*(1.47)*	*(1.81)*	*(2.45)*	*(4.63)*
Greater than 50 hours	0.724	0.755	1.085	1.227	1.176
	(3.13)	*(1.82)*	*(2.14)*	*(2.69)*	*(4.73)*
R bar squared	0.265	0.276	0.188	0.459	0.316
Observations	577	324	237	166	305

The results shown in each table are as a result of estimating equation 6.3′. Although Figure 6.8 showed the standard deviation of hours to increase post 1990, there is no evidence from figures 6.9 to 6.12 that this affected the trend in within-group earnings dispersion, even though the hour bands are always significant across industries (Tables 6.12-6.15). The industries where the hour bands have the largest impact are in Other Manufacturing and Transport and Communication. This finding in Transport and Communication is consistent with the findings of Bell and Hart (1998) where over 4 per cent of full-time male employees in transport occupations were found to work more than 25 hours of overtime per week.

Unfortunately, due to small sample sizes it was not possible to construct more than three hour bands at the industry level. To test the hypothesis further, equation $6.3'$ was estimated for the GB economy as a whole using eight hour band dummy variables: less than 10 hours, 10 to 20 hours, 20 to 30 hours, 30 to 40 hours, 40 to 50 hours, 50 to 60 hours, 60 to 70 hours, and 70 hours plus – where the less than 10 hours was the reference category ($B=7$ in equation $6.3'$).

Table 6.16 Results of using 8 hour bands

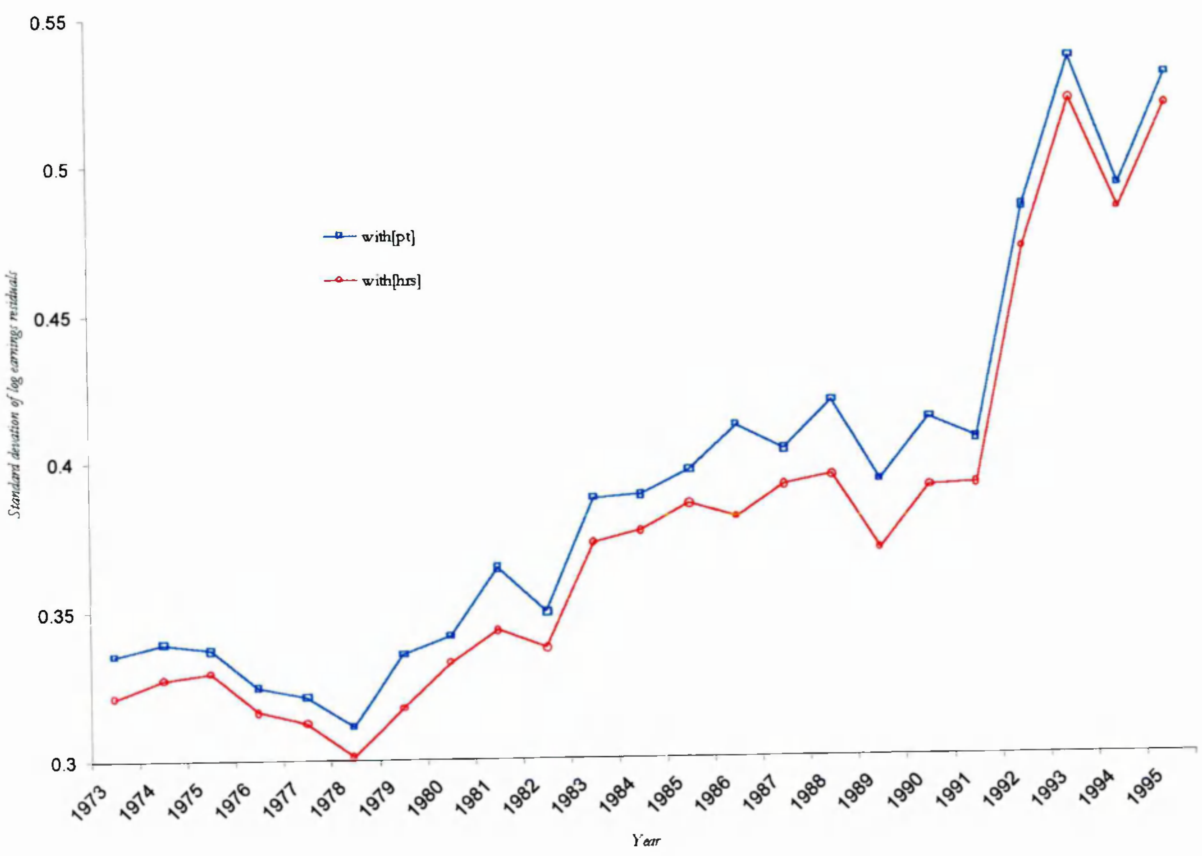
	10-20hrs	20-30hrs	30-40hrs	40-50hrs	50-60hrs	60-70hrs	>70 hrs
1973	0.870**	1.519**	1.948**	1.924**	2.069**	2.161**	2.068**
1974	0.944**	1.518**	1.927**	1.865**	2.013**	2.121**	2.179**
1975	0.492**	1.146**	1.549**	1.502**	1.582**	1.693**	1.685**
1976	0.687**	1.339**	1.876**	1.813**	1.908**	2.017**	1.970**
1977	0.531	1.319**	1.582**	1.569**	1.659**	1.787**	1.755**
1978	0.709**	1.333**	1.709**	1.684**	1.846**	1.878**	1.879**
1979	0.581	1.516**	1.889**	1.854**	1.984**	2.060**	2.075**
1980	0.742**	1.371**	1.946**	1.936**	2.043**	2.059**	1.999**
1981	0.619**	1.689**	1.909**	1.876**	2.101**	1.982**	2.028**
1982	0.818**	1.609**	1.928**	1.901**	2.044**	2.120**	2.108**
1983	1.180**	1.476**	1.859**	1.896**	2.073**	2.024**	1.931**
1984	0.343	1.359**	1.577**	1.589**	1.745**	1.644**	1.640**
1985	0.418	1.168**	1.616**	1.628**	1.787**	1.809**	1.749**
1986	1.461**	2.031**	2.469**	2.537**	2.701**	2.628**	2.752**
1987	0.693**	1.367**	1.978**	2.055**	2.156**	2.171**	2.011**
1988	1.358**	2.094**	2.561**	2.630**	2.768**	2.871**	2.778**
1989	0.750**	1.645**	2.114**	2.172**	2.360**	2.412**	2.474**
1990	1.055**	1.896**	2.453**	2.468**	2.648**	2.699**	2.793**
1991	1.071**	1.861**	2.471**	2.533**	2.691**	2.703**	2.597**
1992	0.768**	1.599**	2.103**	2.159**	2.222**	2.281**	2.111**
1993	1.446**	1.732**	2.358**	2.382**	2.504**	2.477**	2.481**
1994	0.504	1.126**	1.717**	1.721**	1.852**	1.933**	1.796**
1995	0.492	1.259**	1.901**	1.972**	2.117**	2.074**	1.987**

Regressions included 9 industry dummies (agriculture was the reference group)

**Significant at the 5 per cent level or 1 per cent level

The results from using the eight hour bands are shown in Table 6.16, above. In comparison to the reference group of less than 10 hours the other bands always earn more. The coefficients are nearly always significant at the 5 per cent level or better. Those individuals who work longer hours are seen to earn a higher return, although the relationship is not always monotonic. The coefficients tend to grow over time becoming largest in 1991 to 1993 and then declining thereafter – this coincides with the large rise in earnings dispersion (see Figures 6.1 to 6.4)

Figure 6.13 The impact of hour bands on within-group earnings dispersion in Great Britain



With this in mind, figure 6.13, above, looks to see if the hour bands have an impact upon within-group earnings dispersion. Clearly, there is no influence on the trend in earnings dispersion by introducing the hours dummies, although dispersion is lower the trend is not affected. Consequently, the remaining analysis employs the results gained from equation 6.3, that is a simple part-time dummy, since there is no evidence that either industry or economy level earnings dispersion were influenced by changing distribution of hours worker over time. Moreover, it would not be possible to introduce the hours bands for each year at the industry level due to a lack of variation – that is some of the bands would have zero values.

The following section considers the diagnostics of the earnings function in each industry over time.

6.4 Diagnostic and robustness tests

The aim of this section is to test the robustness of the empirical results derived from the first stage of the analysis, shown in Tables 6.1 to 6.8. Issues considered are: (1) misspecification tests of functional form; (2) heteroscedasticity; (3) serial correlation; (4) omitted variable bias; (5) model stability; and (6) the role of outliers.

6.4.1 Functional form

The econometric literature on wage determination has for the most part been based upon semi-log wage equations (Berndt, 1990; Chapter Three, equations 3.2 and 3.3; Chapter Four, equations 4.3 and 4.4). Initially, to test that the semi-log functional form is most appropriate, a misspecification test is applied to equation 4.3 (Chapter Four), following Ramsey (1969, 1970). The misspecification test is applied to each of the four industries for the years 1975, 1985 and 1995. Ramsey (1969, 1970) suggests a test for functional form misspecification - the RESET test - that involves using the squared and cubed identity of the fitted value of the dependent variable from the estimated model, and re-running the regression with the higher order terms as additional parameters. So, from the model introduced in equation 4.4 (Chapter Four) this means regressing the following :

$$\omega_i = X_i\delta + \varepsilon_i \qquad \textbf{(6.4a, 4.4)}$$

then obtaining the fitted values and running :

$$\omega_i = X_i\delta + \hat{\omega}_i^2\varphi + \hat{\omega}_i^3\kappa + \varepsilon_i \qquad \textbf{(6.4b)}$$

The residual sum of squares (RSS) from both models in equations 6.4a and 6.4b are then compared by an F test. In essence, the RESET test considers whether the second regression improves the overall fit of the initial model. The test is calculated :

$$\frac{[\text{RRSS} - \text{URSS}]/(p-1)}{\text{URSS}/(N-k)} \sim F_{p-1,N-k} \qquad \textbf{(6.5)}$$

where RRSS is the residual sum of squares from the restricted model (equation 6.4a), URSS is the residual sum of squares from the unrestricted model (equation 6.4b), p-1 is the number of linear restrictions, N is the number of observations, and k is the number of parameters. The hypothesis tested is :

H_0 The model in equation 6.4a is not misspecified

H_1 The model in equation 6.4a is misspecified

The results of this test for functional form are shown in Table 6.17 below, for each industry in three selected years : 1975, 1985 and 1995.

Table 6.17 Tests of functional form

	1975	*1985*	*1995*
Manufacturing	1.55	1.30	0.59
Other Manufacturing	0.45	0.11	1.17
Construction	5.72	6.22	4.94
Transport and Communication	1.63	1.89	0.46

In each year and industry the null hypothesis cannot be rejected. Consequently, it can be concluded that the appropriate specification is a semi log format, as used extensively in previous econometric work on earnings determination (Willis, 1986; Berndt, 1990).

6.4.2 Tests for heteroscedasticity

The occurrence of heteroscedasticity in the earnings function (equations 4.3 and 4.4, reproduced in 6.4a) could be potentially harmful. A standard assumption of Ordinary Least Squares estimation is that $\mathrm{Var}(\varepsilon_i) = \sigma_i^2 = \sigma^2\pi_i$, and so

$$E\left[\varepsilon\varepsilon'\right] = \sigma^2\Omega = \begin{bmatrix} \sigma_1^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & 0 & \dots & 0 \\ & & \cdot & & \\ & & \cdot & & \\ 0 & 0 & 0 & \dots & \sigma_n^2 \end{bmatrix}$$

which produces an unbiased estimator $\hat{\delta} = \left(X'X\right)^{-1} X'\omega$ if $\pi_i = 1$. This means in the probability limit the estimator $\hat{\delta}$ from the above equation is equal to the true value δ, i.e. $\operatorname*{Plim}_{n \to \infty} \hat{\delta} = \delta$. Given non-homoscedastic errors, however, we have

$$\Omega = \begin{bmatrix} \pi_1 & 0 & 0 & \ldots & 0 \\ 0 & \pi_2 & 0 & \ldots & 0 \\ & & . & & \\ & & . & & \\ 0 & 0 & 0 & \ldots & \pi_n \end{bmatrix}$$

where $\pi_i \neq 1$. In the probability limit the estimator $\hat{\delta}$ from the above equation would not be equal to the true value δ, i.e. $\underset{n \to \infty}{\operatorname{Plim}} \hat{\delta} \neq \delta$. In terms of the measure used for within-group earnings dispersion, this has serious implications, since

$$\underset{n \to \infty}{\operatorname{Plim}} \hat{\varepsilon} = \omega - X\hat{\delta} \neq \varepsilon \qquad \textbf{(6.6)}$$

Because the standard deviation of the residual is used as the measure of inequality, the absence of homoscedasticity would lead to an incorrect estimate of dispersion. Consequently, it is important to test for homoscedasticity, and correct estimates if the model is heteroscedastic. A Lagrange Multiplier test statistic is calculated (following Breusch and Pagan, 1979), where $\sigma_i^2 = \sigma^2\psi(\alpha_0 + X_i\alpha)$. The null hypothesis tested is that the model is homoscedastic, hence :

H_0 Homoscedastic $\alpha=0$

H_1 Otherwise $\alpha\neq0$

Based upon a Lagrange Multiplier test, the test statistic is χ^2~(21) with a critical value of 32.67 at the 5 per cent level of significance and 38.93 at the 1 per cent level. From Tables 6.1 to 6.8 the null hypothesis is rejected in most instances. Consequently, the earnings function estimated in the first stage is heteroscedastic, which means any measure of remaining dispersion may be inflated, as shown in equation 6.6.

To overcome the problem of heteroscedasticity, all estimates in the first stage of the empirical procedure are estimated using Generalised Least Squares - White's technique (White 1980). This works by gaining a consistent estimator of the variance - covariance matrix. More precisely, unbiased point estimators of δ are obtained using OLS, and are then used to estimate Ω as a diagonal matrix with the *i*th squared OLS residual as the *(i,i)*th element in Ω. So,

$$\hat{\Omega} = \begin{bmatrix} \hat{\varepsilon}_1^2 & 0 & 0 & \ldots & 0 \\ 0 & \hat{\varepsilon}_2^2 & 0 & \ldots & 0 \\ & & \cdot & & \\ & & \cdot & & \\ 0 & 0 & 0 & \ldots & \hat{\varepsilon}_n^2 \end{bmatrix}$$

White (1980) then shows that $\underset{n \to \infty}{\mathrm{P\,lim}} \left(X'X\right)^{-1} X'\hat{\Omega}X\left(X'X\right) = \left(X'X\right)^{-1} X'\Omega X\left(X'X\right)^{-1}$ and so heteroscedastic consistent standard errors can be obtained, since $\mathrm{Var}\left(\hat{\delta}_{OLS}\right) = \left(X'X\right)^{-1} X'\hat{\Omega}X\left(X'X\right)^{-1}$. All the t tests reported in Tables 6.1 to 6.8 are based upon heteroscedastic consistent standard errors.

6.4.3 Serial correlation

A further assumption made by the estimating procedure is that all error terms are independent of each other. Whilst heteroscedasticity is most commonly associated with cross sectional data, problems of serial correlation are usually associated with time series data (Greene, 1993), yet the model estimated in the first stage (equation 4.4, 6.4a) is estimated upon cross sectional data year by year. However, an analysis of cross section spatial correlation can be an indicator of possible specification problems in the model, such as omitted variable bias. The test statistic shown in Tables 6.1 to 6.8 is the Durbin-Watson test (1950, 1951) :

$$DW = \frac{\sum_{i=2}^{N} (\hat{\varepsilon}_i - \hat{\varepsilon}_{i-1})^2}{\sum_{i=1}^{N} \hat{\varepsilon}_i^2} \tag{6.7}$$

where $\hat{\varepsilon}_i$ are the residuals from equation 4.4, 6.4a. Because the sample sizes used are reasonably large in each year and industry, the statistic should be close to 2. For those years where the statistic is considerably high or low, further investigation into the earnings specification is undertaken. In particular, in section 6.4.4, years with dubious DW statistics are tested for omitted variables.

6.4.4 Omitted variable bias

Section 6.4.3 introduced the concept of serial correlation, as identified by a significant DW statistic. It is possible that the presence of such correlation can be caused by omitting relevant variables from the earnings function. In this instance the source of serial correlation in the errors is caused through the omission of relevant variables, and those variables are themselves serially correlated. For instance, suppose the model estimated in equation 6.4a is not the true relationship between earnings and worker characteristics. Instead, the true model underlying the determination of earnings is of the following form :

$$\omega_i = X_i\delta + Z_i\psi + \varepsilon_i \tag{6.8}$$

where Z is a vector of omitted variables and $\varepsilon \sim IID(0, \sigma^2)$. If the variables in Z are autocorrelated, then the random error from equation 6.4a, ε_i, will also be autocorrelated, shown by a significantly high or low DW statistic.

Table 6.18 Identification of three years with the highest or lowest DW statistic

	DW, *Year*	DW, *Year*	DW, *Year*
Manufacturing	1.81 *(1984)*	1.82 *(1987)*	1.84 *(1993)*
Other Manufacturing	1.76 *(1976)*	1.59 *(1986)*	2.19 *(1993)*
Construction	1.81 *(1975)*	2.27 *(1986)*	2.11 *(1993)*
Transport and Communication	1.78 *(1973)*	1.84 *(1988)*	2.09 *(1993)*

Table 6.18, above, shows for each of the four industries possible problematic DW statistics (see Tables 6.1 to 6.8), and the DW in 1993 where there is a sharp increase in within-group earnings dispersion in each industry. Regressing ω on X without including Z will lead to a biased estimator, as shown below (Greene, 1993) :

$$\hat{\delta} = \left(X'X\right)^{-1} X'\omega$$

$$= \delta + \left(X'X\right)^{-1} X'Z\psi + \left(X'X\right)^{-1} X'\varepsilon$$

Taking the expectation leads to a biased estimator of δ unless $X'Z = 0$:

$$E\left[\hat{\delta}\right] = \delta + \left(X'X\right)^{-1} X'Z\psi \qquad \textbf{(6.9)}$$

But, more importantly, the omission of a relevant variable will result in a biased estimate of σ_ε^2, which influences the measure of within-group earnings dispersion $v\left(\hat{\varepsilon}\right) = \hat{\sigma}_\varepsilon$. To see this, assume that the relevant variable(s) Z are omitted, which gives a residual ε_1. An estimate of $\sigma_{\varepsilon_1}^2$ is :

$$\hat{\sigma}_{\varepsilon_1}^2 = \frac{\left[\hat{\varepsilon}_1{}'\hat{\varepsilon}_1\right]}{N - k_1}$$

where k_1 is the number of parameters included omitting Z. However, the estimate is biased upwardly since :

$$\hat{\varepsilon}_1 = M_1\omega = M_1(X\delta + Z\psi + \varepsilon) = M_1 Z\psi + M_1\varepsilon$$

where $M_1 = I - X\left(X'X\right)^{-1}X'$ is the idempotent matrix. The expected value of $\hat{\varepsilon}_1'\hat{\varepsilon}_1$ is

$$E\left[\hat{\varepsilon}_1'\hat{\varepsilon}_1\right] = \psi' Z' M_1 Z\psi + (N - k_1)\sigma^2 \qquad \textbf{(6.10)}$$

The first term is positive and so the estimate of $\sigma^2_{\varepsilon_1}$ is biased. In conclusion, the omission of relevant variables from the regression will result in biased estimates of δ and $\sigma^2_{\varepsilon_1}$ (Greene, 1993), as shown in equations 6.9 and 6.10.

The following uses a general Hausman (1978) mis-specification test for omitted variables. Consider, the difference between the two models in equations 6.4a and 6.8 above, where the later is the correct specification. Let $\hat{\delta}$ be the estimator obtained from equation 6.4a by regressing ω on X only, and $\tilde{\delta}$ be the estimator obtained from equation 6.8 by regressing ω on X and Z. Under the assumption that the model of ω on X alone does not contain omitted variables, then the estimator $\hat{\delta}$ is consistent and efficient; however if this model suffers from omitted variables then $\hat{\delta}$ is efficient but inconsistent. If the extended model shown in equation 6.8 is correct then $\tilde{\delta}$ is always consistent. $\hat{\delta}$ is consistent only under the restriction that $\psi = 0$. If $\psi = 0$ the difference between $\hat{\delta}$ and $\tilde{\delta}$ will, asymptotically, have a zero mean and it has been proposed (Hausman 1979) that the test:

$$\left(\hat{\delta} - \tilde{\delta}\right)'\left[\hat{V} - \tilde{V}\right]^{-1}\left(\hat{\delta} - \tilde{\delta}\right) \sim \chi^2(k_1) \qquad \textbf{(6.11)}$$

be used, where $\hat{V}$ and $\tilde{V}$ are the estimated variances of $\hat{\delta}$ and $\tilde{\delta}$ respectively and the statistic is distributed with k_1 (the number of regressors in X) degrees of freedom. However, there is a problem with the statistic in that it is possible the difference between the two variance estimates will be non-singular and positive definite. These problems can be overcome by comparing the two estimates, namely $\hat{\delta} = (X'X)^{-1}X'\omega$ and $\tilde{\delta} = (X'AX)^{-1}X'A\omega$ where A is chosen so that $\tilde{\delta}$ is consistent if the model given in equation 6.4a is true. If the model from equation 6.4a is true then we have $\omega = X\hat{\delta} + \hat{\varepsilon}$ and so :

$$\tilde{\delta} = \hat{\delta} + (X'AX)^{-1}X'A\hat{\varepsilon}$$

The Hausman test for omitted variables is then equivalent to testing that $\psi = 0$ in equation 6.8, where

$$A = I - Z(Z'Z)^{-1}Z'$$

providing that the number of regressors in X is greater than the number of regressors in Z.

The following undertakes a Hausman test to see if the model does in fact suffer from omitted variables. A possible omitted variable in the earnings function is an indicator of occupation. Although occupational groups are available in each year of the General Household Survey, they are inconsistent over time due to changing definitions. Typically, previous studies that have used the General Household Survey in each year have omitted occupational indicators (Blanchflower and Oswald, 1994; Katz, Loveman and Blanchflower, 1995; and Blackaby, Clark, Leslie and Murphy, 1997). For those years indentified in Table 6.18, where the DW statistic indicates possible problems, indicators of occupational groups are included in the earnings function. Five occupational categories are used in each case, indicating whether the individual is (1) a professional employee, (2) a managerial employee, (3) a non-manual employee, (4) a skilled manual employee, or (5) an unskilled manual worker. By using a Wald test of whether these actually are omitted variables the following hypothesis can be tested :

$$H_0 \ \text{No omitted variables}, \ \psi = 0 \ \text{in equation 6.8}$$

$$H_1 \ \text{Otherwise} \ \psi \neq 0$$

The results of the Hausman test for omitted variables are shown in Table 6.19, below. It appears that omitted variable bias is a problem in the earnings function employed, where the null hypothesis is rejected 9/12 at the 5 per cent level. Consequently, it should be remembered that the measure of within-group earnings dispersion will be upwardly biased, as shown in equation 6.10. However, what is important for the second stage of the empirical process is whether omitted variables influence the trend in dispersion.

Table 6.19 A Hausman test for omitted variables

	$\chi^2(1)$	*Year*	$\chi^2(1)$	*Year*	$\chi^2(1)$	*Year*
Manufacturing	10.79**	*1984*	2.48	*1987*	4.69*	*1993*
Other Manufacturing	25.20**	*1976*	4.50*	*1986*	1.39	*1993*
Construction	16.09**	*1975*	4.09*	*1986*	1.76	*1993*
Transport and Communication	29.18**	*1973*	8.25**	*1988*	6.42**	*1993*

** Significant at the 1 per cent level
* Significant at the 5 per cent level

Table 6.20 Changing model performance over time when including omitted variables

	$\overline{R}^2$	*Year*	$\overline{R}^2$	*Year*	$\overline{R}^2$	*Year*
Manufacturing	0.328	*1984*	0.332	*1987*	0.162	*1993*
Other Manufacturing	0.443	*1976*	0.385	*1986*	0.280	*1993*
Construction	0.299	*1975*	0.442	*1986*	0.138	*1993*
Transport and Communication	0.392	*1973*	0.416	*1988*	0.221	*1993*

Considering the cases analysed in Table 6.20 the measure of model fit fell over time even when including the extra occupational variables, see Table 6.15 above. As shown in section 6.3.1 as model performance declines, as measured by $\overline{R}^2$, within-group earnings dispersion will increase. So whilst the model does suffer from omitted variable bias it can be concluded that the trend in within-group earnings dispersion should be unaffected.

The following considers the stability of the earnings function over the twenty-three year period, in particular whether the returns to educational, personal characteristics and regional location have been stable.

6.4.5 Model stability

The method described to disaggregate earnings dispersion into between- and within-group components, using repeated cross sections over a period of time to gain some degree of time series, is highly dependent upon parameter stability. When we estimate an earnings function and use it to construct measures of between-group and within-group earnings dispersion, it is assumed that the parameters are the same over time. This is important for two reasons. Firstly, for model specification over time and, secondly, for making predictions about future trends.

The following introduces a procedure for testing the stability of the coefficients obtained from the first stage of the empirical analysis. Using dummy variables, it is possible to test for equality between sets of coefficients. Pooling the data for 1973 with subsequent years, i.e. 1974, 1975,...,1995 yields to period *t=1* for 1973 with *n1* observations and *t=2* for the subsequent year with *n2* observations. The variables in $\mathbf{D}$ are personal characteristics, $\mathbf{Ed}$ is a vector of qualifications, and $\mathbf{Region}$ controls for earnings differentials due to location (for variable definitions, refer to Chapter Five). Pooling over two years *t1* and *t2* gives:

$$lnW_{it} = \omega_{it} = \lambda_1 + \beta_1 \mathbf{Exp}_{it} + \gamma_1 \mathbf{Exp}_{it}^2 + \sum_{q=1}^{Q} \theta_{1q} \mathbf{D}_{iqt} + \sum_{g=1}^{6} \mu_{1g} \mathbf{Ed}_{igt} + \sum_{h=1}^{10} \eta_{1h} \mathbf{Region}_{iht} +$$

$$\lambda_2 \mathbf{T}_{it} + \beta_2 \mathbf{T}_{it} \mathbf{Exp}_{it} + \gamma_2 \mathbf{T}_{it} \mathbf{Exp}_{it}^2 + \sum_{q=1}^{Q} \theta_{2q} \mathbf{T}_{iqt} \mathbf{D}_{iqt} + \sum_{g=1}^{6} \mu_{2g} \mathbf{T}_{igt} \mathbf{Ed}_{igt} +$$

$$\sum_{h=1}^{10} \eta_{2h} \mathbf{T}_{iht} \mathbf{Region}_{iht} + \varepsilon_{it}$$

$$\varepsilon_{it} \sim \mathrm{IID}(0, \sigma^2), \quad t=1,2$$

From this model it is possible to test for changes in both the intercept and the slope, since in period *t=1* and in period *t=2*

$$\mathrm{E}(\omega_{it} | \mathbf{T} = 0, \mathbf{X}_{it}) = \lambda_1 + \beta_1 \mathbf{Exp}_i + \gamma_1 \mathbf{Exp}_i^2 + \sum_{q=1}^{Q} \theta_{1q} \mathbf{D}_{iq} + \sum_{g=1}^{6} \mu_{1g} \mathbf{Ed}_{ig} + \sum_{h=1}^{10} \eta_{1h} \mathbf{Region}_{ih}$$

$$\mathrm{E}(\omega_{it} | \mathbf{T} = 1, \mathbf{X}_{it}) = (\lambda_1 + \lambda_2) + (\beta_1 + \beta_2) \mathbf{Exp}_i + (\gamma_1 + \gamma_2) \mathbf{Exp}_i^2 + \sum_{q=1}^{Q} (\theta_{1q} + \theta_{2q}) \mathbf{D}_{iq} +$$

$$\sum_{g=1}^{6} (\mu_{1g} + \mu_{2g}) \mathbf{Ed}_{ig} + \sum_{h=1}^{10} (\eta_{1h} + \eta_{2h}) \mathbf{Region}_{ih}$$

Table 6.21 Hypothesis tests for intercept and slope changes

	Null hypothesis H_0 *Stable coefficients t1 to t2*		*Alternative hypothesis* H_1 *Unstable coefficients*	
Intercept	$\lambda_1 - \lambda_2 = 0$		$\lambda_1 - \lambda_2 \neq 0$	
Slope *Experience*	$\beta_1 - \beta_2 = 0$		$\beta_1 - \beta_2 \neq 0$	
Slope *Experience squared*	$\gamma_1 - \gamma_2 = 0$		$\gamma_1 - \gamma_2 \neq 0$	
Slope *Personal effects*	$\theta_{1q} - \theta_{2q} = 0$	q=1...3	$\theta_{1q} - \theta_{2q} \neq 0$	q=1...3
Slope *Educational effects*	$\mu_{1g} - \mu_{2g} = 0$	g=1...6	$\mu_{1g} - \mu_{2g} \neq 0$	g=1...6
Slope *Regional effects*	$\eta_{1h} - \eta_{2h} = 0$	h=1...10	$\eta_{1h} - \eta_{2h} \neq 0$	h=1...10

In the context of an earnings function, the intercept represents earnings with no qualifications or personal characteristics. Similarly, slope coefficients represent returns to observable productivity, such as education or race. Thus, the hypotheses for intercept and slope changes are tested, as shown in Table 6.21. If the null hypothesis is accepted over the alternative hypothesis, then the intercept or slope does not change over the two periods. Such a method has an advantage over the Chow test in that it informs us which coefficient (slope) or intercept is different, where if the t ratio on the interaction terms (that is, $\lambda_2, \beta_2, \gamma_2, \theta_{2q}, \mu_{2g}, \eta_{2h}$) is significant, then the null hypothesis is rejected in favour of the alternative. Applying the dummy variable technique for each industry, it is found that approximately 90 per cent of the parameters are stable. Table 6.22 shows that for those coefficients which are unstable the majority of the problem occurs through changing slope in the regional dummies.

Table 6.22 Overall stability, and instability in the earnings equation.

	Manufacturing	*Other Manufacturing*	*Construction*	*Transport & Communication*
Overall %	**89.5**	**90.46**	**89.04**	**90**
Intercept %	0.72	0.45	0.46	0.68
Personal %	2.86	1.59	3.88	2.05
Education %	3.34	2.5	2.51	3.86
Regional %	3.6	5	4.11	3.41

Having found that the estimates from the first stage of the empirical procedure are 90 per cent stable, the following section discusses another problem which may influence the measure of within-group earnings dispersion that of outliers.

6.4.6 The role of outliers

An outlier is any observation that is substantially different from the rest of the observations. It is possible that the data may contain more than one outlier, where its presence may influence the trend in within-group dispersion. The presence of outliers is detected by analysing the residuals from the earnings function. The years of particular interest are after 1991, where in each industry there are large jumps in dispersion (Figures 6.1 to 6.4). In order to identify outliers in the data set used to estimate the regression from the first stage, of the form $\omega = X\delta + \varepsilon$, the so-called *Hat Matrix* is of particular importance: $H = X\left(X'X\right)^{-1}X'$, where H projects any *nx1* vector into the column space of X. Defining the fitted values from OLS regression as $H\omega$, the least squares residuals are given by $e = M\omega = (I - H)\varepsilon$, where the idempotent matrix $M = I - X\left(X'X\right)^{-1}X'$. The variance matrix of the residuals is given by $E\left[ee'\right] = \sigma^2 M = \sigma^2(I - H)$. From this, it is possible to identify which residuals are significantly large. The residuals should be standardised by dividing by the appropriate standard error for that particular residual. Thus,

$$\frac{e_i}{\left[s^2(1-h_{ii})\right]^{\frac{1}{2}}} = \frac{e_i}{\left(s^2 M_{ii}\right)^{\frac{1}{2}}}$$

where h_{ii} is the *i*th diagonal element of H and s^2 is the OLS estimator of σ^2. The hat matrix provides a measure of 'leverage', since the larger is h_{ii} the smaller the variance of the OLS residual and the larger the standardised residual. Hence, a large value of h_{ii} is an indicator that observation *i* is a potential outlier. The distribution of the residuals are graphed in Appendix A5 and outliers are identified following the above procedure. Figures 6.14 to 6.17 show how the removal of outliers influences within-group earnings dispersion.

Figure 6.14 Within-group dispersion - controlling for outliers in Manufacturing.

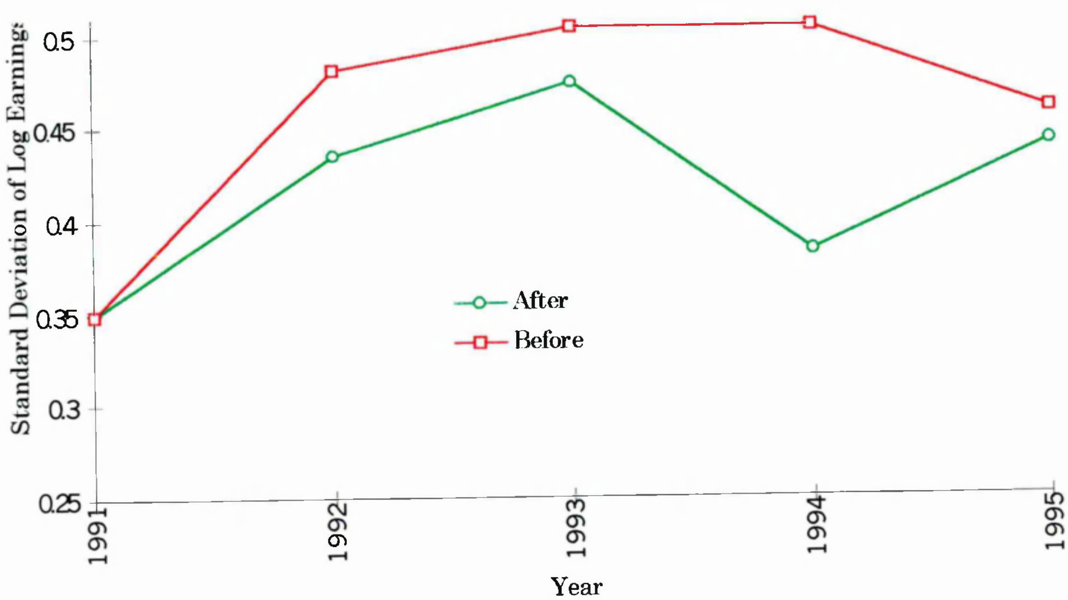


Figure 6.15 Within-group dispersion - controlling for outliers in Other Manufacturing.

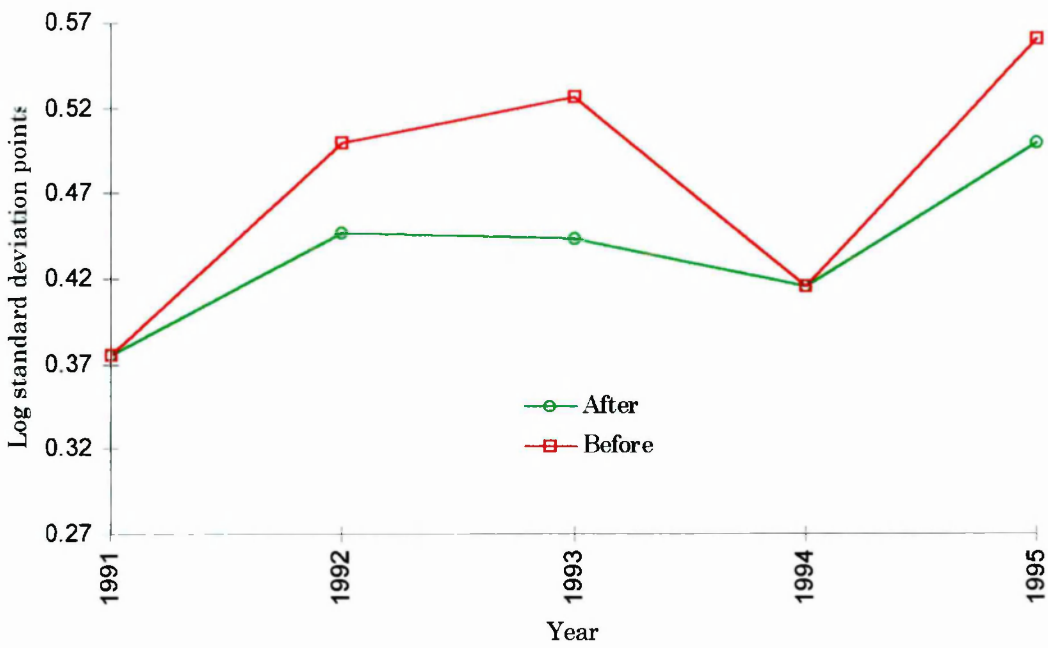


Figure 6.16 Within-group dispersion - controlling for outliers in Construction.

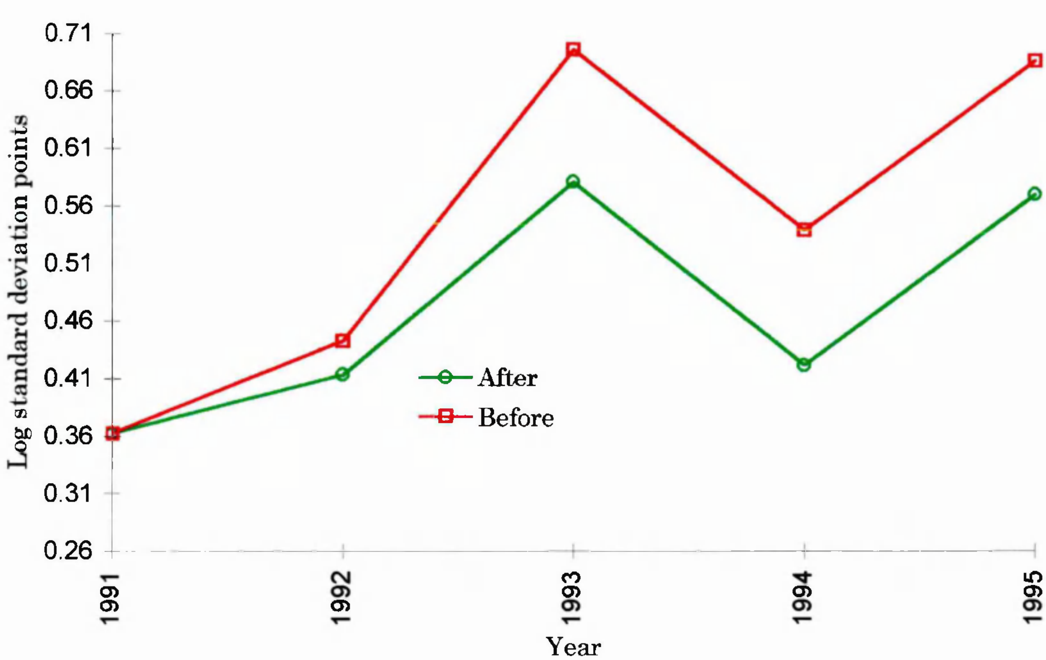
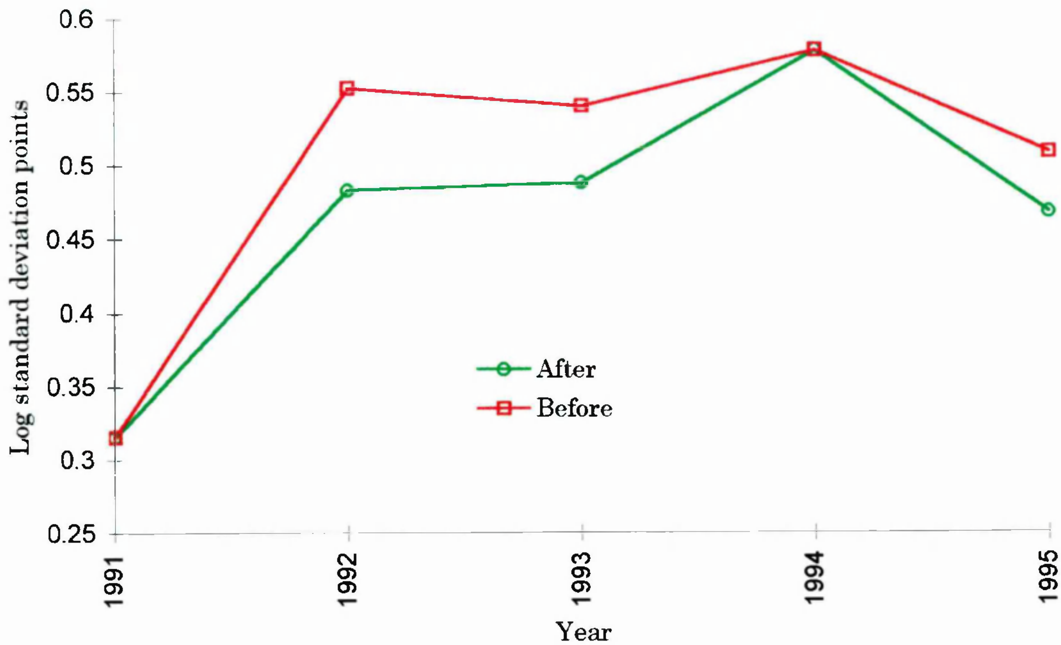


Figure 6.17 Within-group dispersion - controlling for outliers in transport and Communication



The figures reveal that it is important to control for outliers, as not only is the magnitude of within-group earnings dispersion affected, in some industries so is the trend. Consequently, the measure of earnings dispersion adjusted for outliers is preferred.

6.5 Summary

Figures 6.1 to 6.4 revealed that whilst each industry experienced increasing earnings dispersion especially in the 1980s and 1990s, trends in between-group and within-group dispersion differed greatly. Much of the difference was due to the impact of education see Tables 6.1 to 6.8. For instance, in Manufacturing and Construction within-group earnings dispersion remained roughly constant from 1973 to 1983, whilst in the other two industries it fluctuated. This makes a strong argument for analysing industry level trends rather than focusing on just Manufacturing or the economy-wide level. A common event in each industry is the large increase in earnings dispersion in the early 1990s caused by within-group factors. A possible question may be if within-group earnings dispersion follows the trend in overall earnings dispersion, especially in the 1990s, why not just look at overall earnings dispersion instead of controlling for workers' characteristics? Whilst this may be legitimate after the late 1980s, over the period 1973 to 1983 between-group earnings dispersion was largely responsible for the trend in overall earnings dispersion. After the mid 1980s between-group earnings dispersion played less of a role, although was influential in certain years (Figures 6.1 to 6.4). Further, because the sample size for the second stage of the analysis is fairly small at only 23 years any deviation between the trends in overall and within-group earnings dispersion could influence the results. Consequently, it seems reasonable to control for as many factors as possible that could potentially influence earnings dispersion - which is what this chapter has achieved.

Not surprisingly, the results at the industry level corresponded with those found by other authors (Schmitt, 1995; and Machin, 1996[a,b]). In particular, earnings dispersion occurs within narrowly defined groups after the mid-1980s, suggesting relative demand shifted in favour of higher skilled workers - consistent with the findings in Table 6.9 and previous research findings (Levy and Murnane, 1992; Gottschalk and Smeeding, 1997; Schmitt, 1995; Machin, 1996[a,b], and Machin and Van Reenen, 1998). The following chapter now explains the trend in within-group earnings dispersion for each industry, in terms of the key factors identified in the literature (Chapter Two) capable of causing any remaining dispersion.

7

Results from Stage Two - A Time Series Analysis of Wage Dispersion

7.1 Introduction

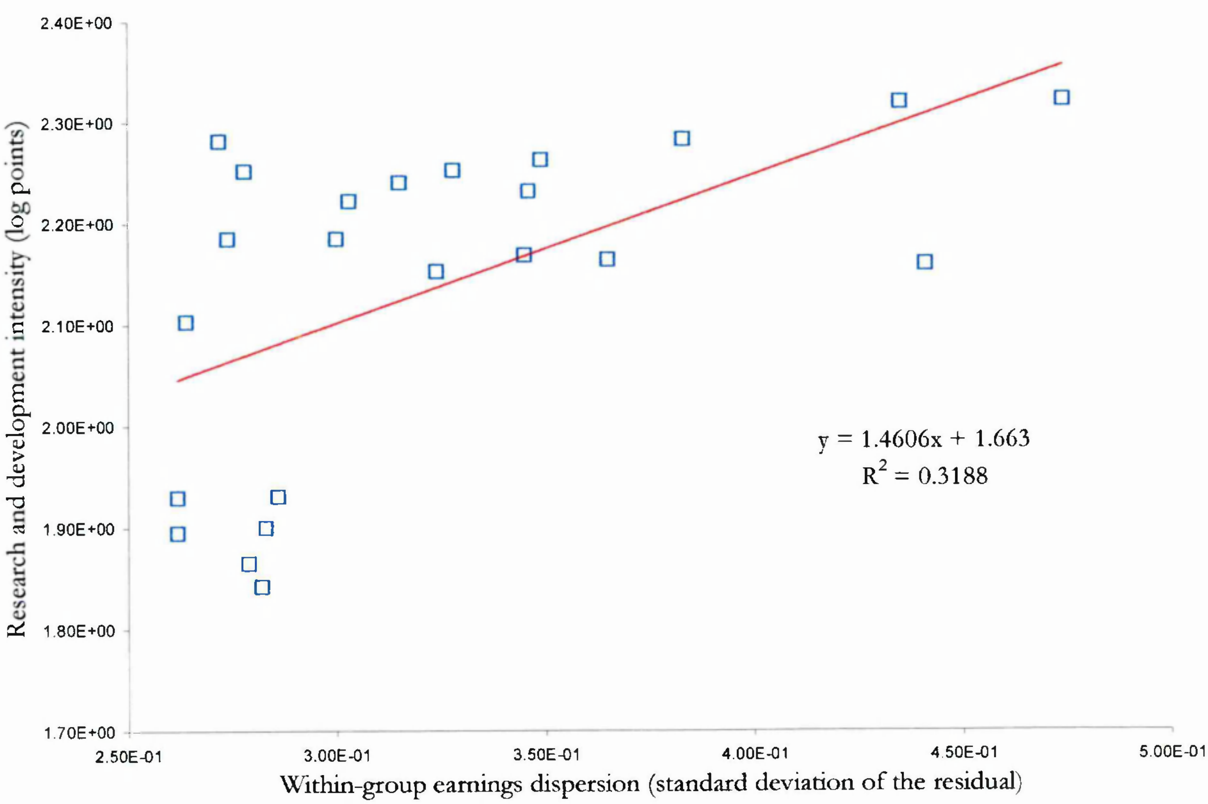
Having controlled for observable factors that may cause earnings dispersion, such as education and personal characteristics, the following analysis provides an explanation of any remaining earnings dispersion. To accomplish this task, industry level data are used to provide proxies for possible factors that may cause within-group earnings dispersion. The main influences capable of explaining within-group earnings dispersion are market forces and institutional changes (Chapters Two and Three). Proxies for the former are: research and development intensiy, trade intensity, female participation and the supply of immigrants. Institutional change is measured by the number of workers involved in strikes. The data employed to proxy such influences has been described in detail in Chapter Five, section 5.3. Plots of data trends are given in Appendix A2 and the values for each year in Appendix A6.

Initially, in section 7.2 the trends in the industry data are investigated. In section 7.3 unit root tests are implemented for within-group earnings dispersion, market force and institutional change data using a number of techniques. This section also looks to see whether the trend in each key theme identified in the literature review can explain within-group earnings dispersion. In section 7.4 the possible impact of market forces and institutional change upon within-group earnings dispersion is investigated. Section 7.5 considers whether market forces and institutional change also influence between-group earnings dispersion, in other words is there an influence upon the return to worker characteristics. Furthermore, tests of whether technology and trade actually influence the returns to education are implemented.

7.2 Trends in the industry data

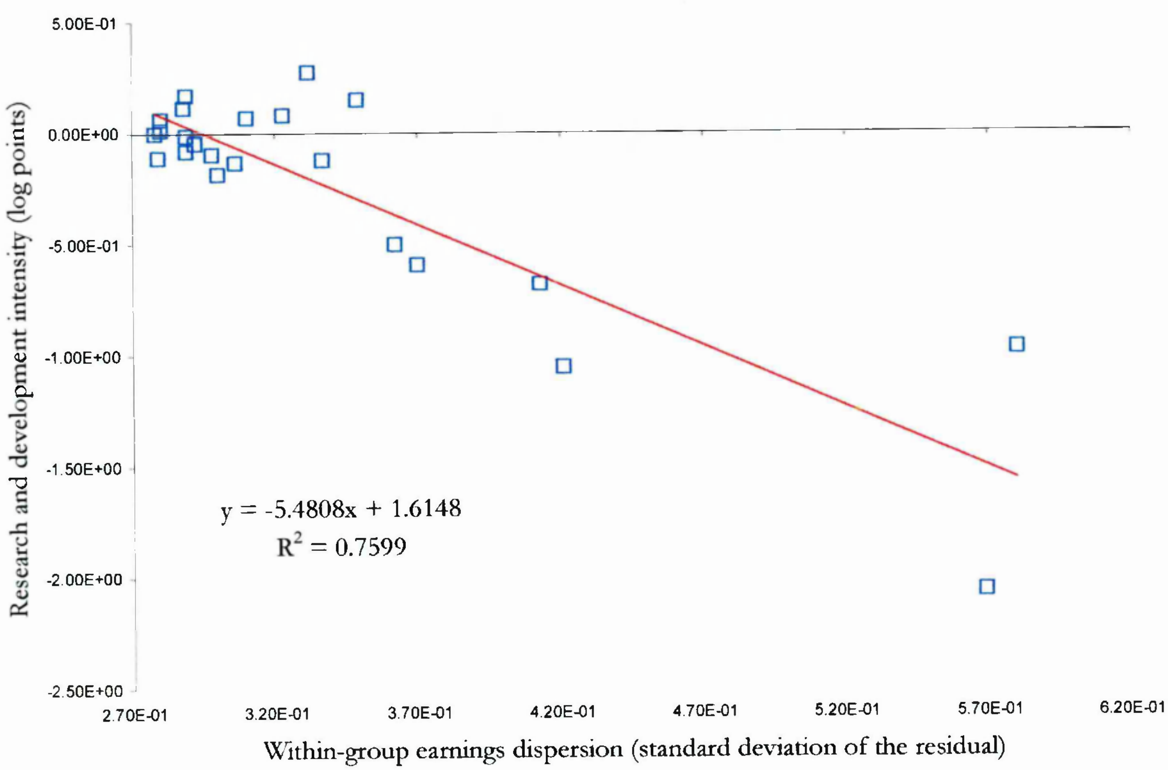
Research and development intensity in Manufacturing rose from just under 6½ per cent in 1973 to over 10 per cent by 1993 (see Appendix A2 and A6).

Figure 7.1 Cross plot of within-group earnings dispersion and research and development intensity – Manufacturing



Given the interpretation that skilled labour and technology are complementary, it would appear that the earnings gap between low- and high-skilled workers should have risen over this period. Indeed, this is exactly what occurred in Manufacturing, where within-group earnings dispersion rose considerably after 1983 (Chapter Six, Figure 6.1). The positive correlation between research and development intensity and within-group earnings dispersion is shown by a simple cross plot of the data and the line of best fit in Figure 7.1, above. The positive correlation, giving an R squared of 0.32 and a slope of 1.46, suggests that rising within-group earnings dispersion occurred at a time when research and development intensity was increasing in Manufacturing, *prima facie* evidence of skill-biased technological change.

Figure 7.2 Cross plot of within-group earnings dispersion and research and development intensity – Construction



Whilst a skill-biased technological change argument for causing within-group earnings dispersion may seem appropriate in Manufacturing, research and development intensity actually fell in the Construction industry from 1.3 per cent in 1986 to 0.3 per cent by 1994, a period where within-group dispersion increased substantially (Chapter Six, Figure 6.3). Consequently, the cross plot shown in Figure 7.2, above, depicts a negative correlation between the two data series, a slope on the line of best fit of –5.48. The contrast between Manufacturing and Construction is evident from comparing the two simple cross plots in Figures 7.1 and 7.2. Whilst in Manufacturing a positive correlation suggests skill-biased technological change, for Construction a negative correlation possibly implies low skill - technology complementarity.

It would seem that, for the Construction industry, after the late 1980s something else might be driving the increase in earnings dispersion. Both female participation and immigration increased over this period. From 1987/88 into the 1990s, female participation grew by roughly 4 per cent, whilst immigration rose by about 3 per cent. If both are considered to be substitutes for low-skilled males (Chapter Two), then this may be a possible cause of rising dispersion.

An alternative explanation for increasing earnings dispersion is the decline in collective bargaining. Consistent with this is the decline in three of the industries (the exception being Other Manufacturing) in the number of workers involved in strikes, notably after the 1970s. For example, in Manufacturing the number of workers involved in strikes fell from 698,401 in 1978 to 108,800 by 1990. Also in Manufacturing and Other Manufacturing globalisation increased, as defined by rising trade intensity.

Having given a descriptive analysis of the trends in the data, a more robust method is used to quantify the impact upon within-group earnings dispersion. Time series techniques are adopted to discover which of the potential causes contributes to within-group earnings dispersion. This follows in the footsteps of previous research - where time series methods have been used to investigate earnings dispersion (Borjas and Ramey, 1994; Leslie and Pu, 1995, 1996; Buckberg and Thomas, 1996; Chapter Three, sections 3.2.1 and 3.3).

7.3 Orders of integration, bi-variate cointegration and causation

In sub-section 7.3.1 the data are tested for unit roots using a variety of techniques. Following stationarity tests, sub-section 7.3.2 considers whether each key theme identified from the literature review actually follow the same trend as within-group earnings dispersion. More specifically, we test for bi-variate cointegration. If any of the data do actually cointegrate with within-group earnings dispersion, this is only evidence of a correlation not causation. Consequently, Granger causality tests are employed (Granger, 1969) to consider whether technological change, globalisation, female participation, immigration and institutional change cause within-group earnings dispersion or vice versa.

7.3.1 Unit root tests

Because of the problems associated with differing levels of non-stationary data the following tests to see if the measure of within-group earnings dispersion, market forces and institutional change data exhibit unit roots (Chapter Four, section 4.4). The results of stationarity tests based upon the ADF procedure (Chapter Four, section 4.4, equation 4.7) are shown in Table 7.1, below. The first column tests the null hypothesis that the data contains a unit root by considering the data in levels. The null hypothesis cannot be rejected for any of the data and so is non-stationary.

Table 7.1 Stationarity tests

Industry, Variable	*Unit root tests levels*	*Unit root tests 1st differences*	*Unit root tests 2nd differences*
Manufacturing			
Within-group earnings dispersion	2.54 ∴ not I(0)	5.91** ~ I(1)	*na*
R&D intensity	1.16 ∴ not I(0)	2.69 ∴not I(1)	6.17** ~ I(2)
Strikes	1.49 ∴ not I(0)	7.62** ~ I(1)	*na*
Trade intensity	2.65 ∴ not I(0)	4.70** ~ I(1)	*na*
Female participation	1.79 ∴ not I(0)	5.62** ~ I(1)	*na*
Immigration	2.51 ∴ not I(0)	8.00** ~ I(1)	*na*
Other Manufacturing			
Within-group earnings dispersion	2.68 ∴ not I(0)	5.36** ~ I(1)	*na*
R&D intensity	2.25 ∴ not I(0)	4.31** ~ I(1)	*na*
Strikes	2.56 ∴ not I(0)	4.81** ~ I(1)	*na*
Trade intensity	1.33 ∴ not I(0)	2.47 ∴not I(1)	4.63** ~ I(2)
Female participation	2.55 ∴ not I(0)	4.26** ~ I(1)	*na*
Immigration	3.77 ∴ not I(0)	6.11** ~ I(1)	*na*
Construction			
Within-group earnings dispersion	1.15 ∴ not I(0)	8.85** ~ I(1)	*na*
R&D intensity	1.22 ∴ not I(0)	2.50 ∴not I(1)	5.61** ~ I(2)
Strikes	3.14 ∴ not I(0)	6.21** ~ I(1)	*na*
Female participation	2.75 ∴ not I(0)	4.22* ~ I(1)	*na*
Immigration	3.77 ∴ not I(0)	6.74** ~ I(1)	*na*
Transport & Communication			
Within-group dispersion	1.46 ∴ not I(0)	7.09** ~ I(1)	*na*
R&D intensity	2.24 ∴ not I(0)	3.08 ∴not I(1)	5.28** ~ I(2)
Strikes	1.44 ∴ not I(0)	6.14** ~ I(1)	*na*
Female participation	2.79 ∴ not I(0)	5.35** ~ I(1)	*na*
Immigration	2.87 ∴ not I(0)	6.58** ~ I(1)	*na*

** Significant at the 1 per cent level
* Significant at the 5 per cent level

To consider the order of integration, the middle column tests for stationarity by considering the data in first difference form. Looking down the column it can be seen that, with the exception of research and development intensity (other than in Other Manufacturing) and trade intensity in Other Manufacturing, that the data are now stationary. Rather, the statistics reported are significant at either the 5 per cent level or, more commonly, the 1 per cent level. The significance of the statistics in the middle column indicate that nearly all the data are stationary once they are first differenced and so they are integrated to the first order I(1). The exception is research and development intensity which is integrated to I(2) (excluding Other Manufacturing) and trade in Other Manufacturing which is also I(2). In those instances where research and development intensity and trade intensity do not become stationary after first differencing, the measure of technological change and trade are differenced again so that they become I(1)[1] as shown in the final column of Table 7.1.

There are particular problems associated with the ADF test, one being that the null hypothesis is non-stationarity rather than stationary data. That is, the null hypothesis of non-stationary data was accepted in Table 7.1, however, it may have been accepted when false - a type two error. Given that the unit root is the null hypothesis under the ADF test it is unlikely to be rejected unless there is strong evidence against it. An alternative approach which may be considered more robust is to make the presence of a unit root the alternative hypothesis. The method proposed by Johansen and Juselius (1992) can be used to carry out

[1] Where the indicators technological change and trade intensity are non-stationary after first differencing they have to be differenced twice, because although it is possible to have a mixture of different ordered variables in the model, i.e. I(1) and I(2), there would have to be at least one more I(2) variable. For example, take three variables : $y_t \sim I(1)$, $x_t \sim I(2)$, and $z_t \sim I(2)$, then as long as we can find a cointegrating relationship between x_t and z_t such that $v_t = (x_t - \lambda z_t) \sim I(1)$, it is possible that v_t can potentially cointegrate with y_t to obtain $w_t = (y_t - \varphi v_t) \sim I(0)$. Hence the three variables are cointegrated. It is not possible to include research and development intensity in its I(2) format, because from Table 7.1 it can be seen there is no other I(2) variable for it to cointegrate down to an I(1) level, likewise for trade. Hence the measures are differenced to become I(1) and so the possibility of cointegration with other I(1) variables becomes possible. This is standard practice is time series econometric (Harris, 1995), as there is no software available for analysing I(2) data - although theory has been developed Johansen (1992).

such a test. This is a particular type of unit root test using a multi-variate form of the Augmented Dickey Fuller test, with a null hypothesis of stationarity rather than the usual non-stationary null. In particular from Chapter Four, section 4.4, equation 4.9, we defined $y_t = [v(\hat{\varepsilon}), TC, G, FP, IM, IC]_t'$ in Manufacturing and Other Manufacturing (see footnote 3 for variable definitions). In Construction and Transport and Communication, the non-tradable sectors of the economy, $y_t = [v(\hat{\varepsilon}), TC, FP, IM, IC]_t'$. The test of stationary versus non stationary data is based upon:

$$H_\beta : \beta = (H_1\varphi_1, H_2\varphi_2, \ldots.., H_r\varphi_r) \qquad \textbf{(7.1)}$$

where the matrices $H_1, \ldots.., H_r$ express the linear hypothesis to be tested on each of the *r* possible cointegration relations (see section 7.4, below) and are $(n \times s_i)$ in size, and each φ_i is an $(s_i \times 1)$ vector of parameters to be estimated in the *i*th cointegration relation, with s_i unrestricted parameters. Thus, to test for stationarity the following hypotheses are conducted:

$H_{6,1} = [1,0,0,0,0,0]'$, this amounts to a test of whether $v(\hat{\varepsilon})$, i.e. within-group earnings dispersion, is stationary, and outside of Manufacturing and Other Manufacturing: $H_{5,1} = [1,0,0,0,0]'$. Likewise, to test each of the remaining variables:

$$H_{6,2} = [0,1,0,0,0,0]', H_{6,3} = [0,0,1,0,0,0]', H_{6,4} = [0,0,0,1,0,0]',$$

$$H_{6,5} = [0,0,0,0,1,0]', H_{6,6} = [0,0,0,0,0,1]'$$

Table 7.2 Alternative unit root tests with a null hypothesis of stationary data

Industry, variable	H_0 Stationary, H_1 Otherwise	
	Johansen	**KPSS**
Manufacturing		
Within-group earnings dispersion	45.193***	0.3031***
Research and development intensity	61.780***	0.1376*
Strikes	52.249****	0.1435*
Trade intensity	67.657***	0.8682***
Female participation	52.226***	0.3015***
Immigration	37.581***	0.2992***
Other Manufacturing		
Within-group earnings dispersion	29.403***	0.3032***
Research and development intensity	34.056***	0.1231*
Strikes	45.692***	0.1823**
Trade intensity	32.165***	0.1539**
Female participation	46.745***	0.3022***
Immigration	35.614***	0.3004***
Construction		
Within-group earnings dispersion	19.264***	0.3028**
Research and development intensity	40.737***	0.1223*
Strikes	19.294***	0.2307***
Female participation	26.129***	0.2962***
Immigration	17.629***	0.2957***
Transport and communication		
Within-group earnings dispersion	7.79*	0.302***
Research and development intensity	36.36***	0.1577**
Strikes	20.826***	0.1393*
Female participation	25.02***	0.3013***
Immigration	17.354***	0.299***

* Significant at the 10 per cent level ** Significant at the 5 per cent level
*** Significant at the 1 per cent level

and in Construction and Transport and Communication:

$$H_{5,2} = [0,1,0,0,0]', H_{5,3} = [0,0,1,0,0]', H_{5,4} = [0,0,0,1,0]', H_{5,5} = [0,0,0,0,1]'$$

The resulting statistic is distributed as $\chi^2(n-r)$, shown in Table 7.2, above. In all cases the null hypothesis of a stationary variable can be rejected at the 1 per cent level, with the exception of within-group earnings dispersion in Transport and Communication at the 10 per cent level. Consequently, based upon the multi-variate tests of unit roots proposed by Johansen and Juselius (1992), the results shown in Table 7.2 support those in Table 7.1 based upon the Augmented Dickey Fuller approach and suggest that the results are not prone to Type 2 errors.

A further problem with the Augmented Dickey Fuller test is that the results may be distorted because of the small sample size. Kwiatkowski, Phillips, Schmidt and Shin (1992) (hereafter KPSS) propose a test for unit roots, where the asymptotic validity of the test holds for fairly small samples, such as T<30. If the lag length in the test is set at zero, tests will not be subject to size distortion. As with the Johansen test for unit roots, discussed above, the null hypothesis is of stationary data and so will not be rejected unless there is strong evidence in contrast to the usual case of non-stationary data. The test proceeds as follows. For any time series z_t it is possible to decompose it into three separate components: a time trend, a non-stationary component and a stationary error term. Thus:

$$z_t = \theta T + \varsigma_t + \lambda_t \tag{7.2}$$

$$\varsigma_t = \varsigma_{t-1} + g_t \tag{7.3}$$

where ς_t is the non-stationary component of z_t, g_t is $IID(0,\sigma_g^2)$, T is a time trend and λ_t is a stationary error term. If $\sigma_g^2 = 0$, then z_t will be stationary. Thus, from equations 7.2 and 7.3,

$$z_t = \varsigma_0 + \theta T + \Pi_t \tag{7.4}$$

where $\Pi_t = \sum_{c=1}^{t} g_c + \lambda_t$. Consequently, z_t is stationary if, and only if, Π_t is stationary. The statistic for testing that z_t is stationary with a trend is given by:

$$LM = T^2 \sum_{t=1}^{T} \frac{S_t^2}{\Theta^2(\tau)} \tag{7.5}$$

where S_t is the partial sum process of the residuals from running the regression 7.4, so $S_t = \sum_{i=1}^{T} \hat{\Pi}_i$, and

$$\Theta^2(\tau) = T^{-1} \sum_{t=1}^{T} \hat{\Pi}_t^2 + 2T^{-1} \sum_{\gamma=1}^{s} \Gamma\left(\frac{\gamma}{\tau}\right) \sum_{t=\gamma+1}^{T} \hat{\Pi}_t \hat{\Pi}_{t-\gamma} \tag{7.6}$$

$\Gamma(.)$ is the quadratic kernel with the associated automatic plug in bandwidth parameter τ (Andrews, 1991)[2]. The results shown in Table 7.2 under the column heading KPSS reject the null hypothesis of stationary data in each instance, usually at the 1 or 5 per cent level. Hence, both the Johansen test and the KPSS test for unit roots reject the null hypothesis of stationary data, supporting the standard Augmented Dickey Fuller test.

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[2] The quadratic kernel used is based upon a QS kernel, with $\tau = 1.3221(\hat{\alpha} \times T)^{1/5}$. It is possible to approximate $\hat{\alpha}$ by regressing an AR(1) model for each element $\hat{\Pi}_{at}$ with $a = 1 \ldots \rho$. Let $\hat{\rho}_a, \hat{\sigma}_a^2$ represent the autoregressive and innovation variance estimates for the *a*th element. Then $\hat{\alpha} = \sum_{a=1}^{\rho} \frac{4\hat{\rho}_a^2 \hat{\sigma}_a^2}{(1-\hat{\rho}_a)^8} \div \sum_{a=1}^{\rho} \frac{\hat{\sigma}_a^2}{(1-\hat{\rho}^2)^4}$.

A final specification check regarding unit root testing is whether the time lag used is long enough to produce residuals with no serial correlation - an important assumption for unit root testing. Consider a simple data generating process (dgp), where a variable is generated by the following AR1 process:

$$z_t = \rho z_{t-1} + \Omega_t \tag{7.7}$$

Thus, current levels of z_t are influenced by past values z_{t-1} and a random error term Ω_t. The variable z_t will be stationary if $|\rho| < 1$ (Chapter 4, section 4.4). If $\rho = 1$, then z_t is non-stationary. Each of the unit root tests reported in Tables 7.1 and 7.2 assume that the residual Ω_t is white noise, containing no serial correlation. This may be a source of specification error in the cointegration model, because only a lag length of one time period is used due to the small sample size. A simple test of this assumption is based upon the Ljung-Box statistic (Ljung and Box, 1979):

$$Q = T\sum_{j=1}^{L} r_j^2 \tag{7.8}$$

where $r_j = \dfrac{\sum_{t=j+1}^{T} \Omega_t \Omega_{t-j}}{\sum_{t=1}^{T} \Omega_t^2}$. This statistic is distributed as χ^2 with L degrees of freedom. The hypothesis tested is:

H_0 No autocorrelation

H_1 Otherwise

If the Q statistic is significant then the null hypothesis is rejected in favour of the alternative. Table 7.3, below, shows the results for each variable.

Table 7.3 Ljung-Box Q test on unit root residuals

Industry, variable	Q statistic $\chi^2(1)$
Manufacturing	
Within-group earnings dispersion	0.2027
Research and development intensity	0.3026
Strikes	0.8597
Trade intensity	0.4986
Female participation	0.0748
Immigration	0.0326
Other Manufacturing	
Within-group earnings dispersion	0.1995
Research and development intensity	0.2376
Strikes	0.0009
Trade intensity	0.4172
Female participation	0.1029
Immigration	0.0062
Construction	
Within-group earnings dispersion	0.3413
Research and development intensity	0.1774
Strikes	0.1033
Female participation	0.0199
Immigration	0.0016
Transport and Communication	
Within-group earnings dispersion	0.0877
Research and development intensity	0.2631
Strikes	0.2509
Female participation	0.0169
Immigration	0.0544

At the 75 per cent level of significance $\chi^2(1) = 0.1$

Clearly, at any reasonable level of significance the null hypothesis cannot be rejected (only at the 75 per cent level), consequently, we can be assured that even with a lag length of one serial correlation is not a problem.

7.3.2 Bi-variate cointegration and causality

Having discovered that the data are non-stationary, the following considers whether the trend in within-group earnings dispersion is related to each market force and institutional change variable. In other words, for each industry we consider whether within-group earnings dispersion is cointegrated with each possible explanation in a bi-variate manner (see Chapter Four, section 4.4)[3] . The results of bi-variate cointegration tests are shown in Table 7.4, below. At the 5 per cent level, it is found that each market force and institutional change measure cointegrates with within-group dispersion and more commonly at the 1 per cent level. This means that statistical evidence shows that the trend in within-group earnings dispersion is influenced by each possible explanation considered at the 5 per cent level.

[3] Following earlier notation (Chapter Four), $\nu(\hat{\varepsilon})_t$ is within-group earnings dispersion, technological change (**TC**), globalisation (**G**), female participation (**FP**), immigration (**IM**) and institutional change (**IC**). Given the data is all I(1) then bi-variate cointegration implies $\left[\nu(\hat{\varepsilon})_t - \pi_1 TC_t\right]$~I(0), $\left[\nu(\hat{\varepsilon})_t - \pi_2 G_t\right]$~I(0), $\left[\nu(\hat{\varepsilon})_t - \pi_3 FP_t\right]$~I(0), $\left[\nu(\hat{\varepsilon})_t - \pi_4 IM_t\right]$~ I(0), and $\left[\nu(\hat{\varepsilon})_t - \pi_5 IC_t\right]$~I(0).

Table 7.4 Bi-variate cointegration tests and Granger causality .

Industry, Variable	*Bi-variate cointegration Engle- Granger two step approach.*	*Granger causality* $\chi^2(p)$ $H_0: z \leftrightarrow v(\hat{\varepsilon})$ H_1: Otherwise
Manufacturing		
R&D intensity	3.52** ~ I(0)	7.8**
Strikes	4.13** ~ I(0)	11.22**
Trade intensity	3.21* ~ I(0)	5.82*
Female participation	4.38** ~ I(0)	9.68**
Immigration	3.27* ~ I(0)	9.51**
Other Manufacturing		
R&D intensity	3.73** ~ I(0)	8.88**
Strikes	4.56** ~ I(0)	12.12**
Trade intensity	3.69** ~ I(0)	9.22**
Female participation	3.50** ~ I(0)	9.66**
Immigration	3.68** ~ I(0)	8.51**
Construction		
R&D intensity	3.74** ~ I(0)	12.71**
Strikes	2.83** ~ I(0)	11.81**
Female participation	2.97** ~ I(0)	12.63**
Immigration	3.09** ~ I(0)	17.85**
Transport & Communication		
R&D intensity	3.38* ~ I(0)	5.38*
Strikes	4.13** ~ I(0)	11.25**
Female participation	3.19** ~ I(0)	20.24**
Immigration	3.18** ~ I(0)	16.1**

** Significant at the 1 per cent level
* Significant at the 5 per cent level

The above found the data to be non-stationary and each key theme in the literature cointegrated with within-group earnings dispersion. Such a bi-variate relationship suggests correlation between within-group earnings dispersion and each demand, supply and institutional change variable, but states nothing about causation. For example, does technological change cause greater inequality or vice versa? However, it is possible to test for causation effects by following Granger (1969). Specifically, z is a Granger cause of $v(\hat{\varepsilon})$, if present $v(\hat{\varepsilon})$ can be predicted with a greater degree of accuracy by using past levels of z rather than by not doing so. Consider a model describing within-group earnings dispersion in an unrestricted VAR, that is describing a relationship between two variables $v(\hat{\varepsilon})$ and z. This equation can be written as:

$$v(\hat{\varepsilon})_t = \alpha + \sum_{p=1}^{k} \Lambda_p v(\hat{\varepsilon})_{t-p} + \sum_{p=1}^{k} \Xi_p z_{t-p} + \mu_t \qquad \textbf{(7.9)}$$

If $\Xi_1 = \Xi_2 = ... = \Xi_p = 0$ then, in light of the above definition z does not cause $v(\hat{\varepsilon})$[4], this is given as the null hypothesis. This can be tested by regressing within-group earnings dispersion on a deterministic component α and its own lagged values, so:

$$v(\hat{\varepsilon})_t = \alpha + \sum_{p=1}^{k} \Lambda_p v(\hat{\varepsilon})_{t-p} + e_t \qquad \textbf{(7.10)}$$

Taking the residuals from equation 7.10 and regressing against all the explanatory variables which appear in equation 7.9, yields:

$$\hat{e}_t = \alpha + \sum_{p=1}^{k} \ell_p v(\hat{\varepsilon})_{t-p} + \sum_{p=1}^{k} \delta_p z_{t-p} + \Theta_t \qquad \textbf{(7.11)}$$

[4] This is written as $z \leftrightarrow v(\hat{\varepsilon})$ in Table 7.4, which means causation is indeterminate.

By finding the coefficient of determination for the above, R^2, it is possible to test the null hypothesis by forming a Lagrange multiplier statistic:

$$LM = T \times R^2 \tag{7.12}$$

which under the null hypothesis has a $\chi^2(p)$ distribution, where T is sample size. The results are shown in the final column of Table 7.4 where in all instances it is found that causation runs from $z \rightarrow v(\hat{\varepsilon})$ as we would expect from theory – usually at the 1 per cent level

This section found that the data is non-stationary using a number of tests and that the trend in within-group earnings dispersion is cointegrated in a bi-variate manner with each potential explanatory factor. Moreover, causation runs from the potential explanation to within-group earnings dispersion as expected.

7.4 Multi-variate cointegration

Consequently, it is now possible to include all potential causes of within-group earnings dispersion in a multi-variate model (see Chapter Four, section 4.4). This will indicate which factor out of market forces (demand and supply) and institutional change was the most significant in influencing within-group earnings dispersion. A theoretical issue about the impact of R&D intensity upon earnings dispersion is that if this generates technical change is there a time lag involved in the process? The cointegration analysis can deal with this issue to an extent, since the underlying VAR has each variable lagged by 1 year – it was not possible to include greater lag lengths due to insufficient observations.

7.4.1 Identification of a cointegrating relationship

Table 7.5 gives the results of the number of cointegrating relationships found, based upon Johansen (1988), introduced in Chapter Four, section 4.4. Cointegration rank is tested in Table 7.5, based upon equations 4.14 and 4.15 in Chapter Four. The Trace statistic (derived from equation 4.14) is significant at the 1 per cent level in each industry. Tests for a rank higher than one are firmly rejected by the Trace statistics in each industry and so there is one cointegrating relationship.

Table 7.5 Tests of cointegrating rank adjusted for sample size

Industry	$H_0: r = 0$ no cointegration $H_1: r \leq 1$ cointegration, rank less than/equal to one		$H_0: r = 1$ cointegration rank equal to one $H_1: r \leq 2$ cointegration, rank less than/equal to two	
	$\lambda_{Trace[T-nk]}$	$\lambda_{Max[T-nk]}$	$\lambda_{Trace[T-nk]}$	$\lambda_{Max[T-nk]}$
Manufacturing	100.3^{**}	52.75^{**}	47.59	23.86
Other Manufacturing	120.2^{**}	40.01^{*}	45.83	26.44
Construction	93.66^{**}	44.23^{**}	49.43	20.81
Transport & Communication	89.32^{**}	38.83^{*}	50.48	26.75

Significant at the *5 per cent level, **1 per cent level, based upon distributions from Osterwald-Lenum (1992). Manufacturing and Other Manufacturing include a constant in I(0) space, whilst Construction and Transport & Communication include a constant and trend in I(0) space.

The maximal eigenvalue test (based upon equation 4.15) suggests yet again a rank of one in each industry, although at a lower level of significance in Other Manufacturing and Transport and Communication at 5 per cent.

Having confirmed that the data are cointegrated, Table 7.6, below, reports a variety of diagnostic tests to judge the adequacy of the specification underlying the cointegration approach in each industry.

Table 7.6 Model evaluation diagnostics

Industry, variable	AR	ARCH	HET	NORM
Manufacturing	F[1,12]	F[1,11]	F[11,1]	χ^2[12]
Within-group earnings dispersion	0.768	0.004	1.709	1.684
Research and development intensity	1.813	0.284	0.921	2.473
Strikes	0.001	0.033	2.399	0.024
Trade intensity	1.302	4.135	2.958	1.582
Female participation	0.588	0.086	2.732	0.549
Immigration	0.006	0.362	0.289	5.258
Multi-variate tests	$F_{[AR]}(36,11)=0.872$,		$\chi^2_{[NORM]}(12)=14.08$	
Other Manufacturing	F[1,13]	F[1,12]	F[12,1]	χ^2[12]
Within-group earnings dispersion	3.280	0.733	0.041	5.455
Research and development intensity	1.601	0.843	0.216	1.370
Strikes	0.357	4.016	0.185	0.029
Trade intensity	1.601	1.024	0.085	0.548
Female participation	0.018	0.163	0.432	0.344
Immigration	0.003	1.267	0.123	1.209
Multi-variate tests	$F_{[AR]}(36,15)=0.935$,		$\chi^2_{[NORM]}(12)=10.29$	
Construction	F[1,11]	F[1,10]	F[10,1]	χ^2[10]
Within-group earnings dispersion	0.000	0.535	0.431	3.360
Research and development intensity	0.839	0.167	0.109	0.023
Strikes	0.229	0.506	0.122	4.155
Female participation	0.023	0.263	0.157	1.412
Immigration	0.819	0.233	0.031	1.028
Multi-variate tests	$F_{[AR]}(25,12)=2.002$,		$\chi^2_{[NORM]}(10)=11.45$	
Transport & Communication	F[1,11]	F[1,10]	F[10,1]	χ^2[10]
Within-group earnings dispersion	0.979	0.119	0.063	1.538
Research and development intensity	5.518*	0.002	0.178	3.123
Strikes	3.818	0.597	0.038	0.828
Female participation	2.451	1.445	0.329	1.511
Immigration	1.348	0.007	0.074	1.432
Multi-variate tests	$F_{[AR]}(25,12)=1.369$,		$\chi^2_{[NORM]}(10)=10.28$	

*Significant at the 10 per cent level

In particular, each variable is tested for autocorrelation (AR) , heteroscedasticity (HET), auto-regressive conditional heteroscedasticity (ARCH) – each distributed as an F[p,q] statistic – and normality (NORM) distributed as a χ^2[s]. Also, tests of autocorrelation, distributed as an F[p,q] statistic, and normality distributed as a χ^2[s], each in multi-variate form are reported for each industry. The results show that at both the 1 per cent and 5 per cent levels of significance all the diagnostics can be passed in each industry. Moreover, the corresponding vector tests are also insignificant. This suggests that the single cointegrating vector identified in Table 7.5 is based upon a satisfactory model. These formal tests reported in Table 7.6, above, suggest few major specification problems and that we can go on to investigate the role of demand, supply and institutional change impacts upon within-group earnings dispersion with confidence.

7.4.2 Magnitudes - significance of demand, supply and institutional change

Having found a single cointegrating relationship between the mix of factors able to cause the variation in within-group earnings dispersion, the following shows the cointegrating vector in each industry. This will enable us to determine which factor is most able to explain the trend in within-group earnings dispersion. The cointegrating relationship is shown in Table 7.7, below. Column one gives the results for Manufacturing, the second column Other Manufacturing, the third column Construction, and the final column Transport and Communication. Looking down each column, the coefficients represent the magnitude of the impact upon within-group earnings dispersion. Thus, for Manufacturing the cointegrating vector is $\{1\phi_1\phi_2\gamma_1\gamma_2\tau\}$, where the impact for research and development is captured by ϕ_1, globalisation by ϕ_2, female participation by γ_1, immigration by γ_2, and institutional change by τ.

Table 7.7 Results from Johansen cointegration approach

	Manufacturing	*Other Manufacturing*	*Construction*	*Transport and Communication*
	$\{1\phi_1\phi_2\gamma_1\gamma_2\tau\}$	$\{1\phi_1\phi_2\gamma_1\gamma_2\tau\}$	$\{1\phi_1\gamma_1\gamma_2\tau\}$	$\{1\phi_1\gamma_1\gamma_2\tau\}$
Demand				
R&D intensity ϕ_1	0.452 *(3.2)*	1.429 *(5.5)*	0.279 *(4.4)*	0.041 *(2.9)*
Trade intensity ϕ_2	0.614 *(8.2)*	3.045 *(9.4)*	*na*	*na*
Supply				
Females γ_1	0.299 *(4.1)*	0.439 *(2.2)*	0.047 *(0.9)*	0.079 *(2.9)*
Immigrants γ_2	0.291 *(6.4)*	0.958 *(7.0)*	0.252 *(6.9)*	0.071 *(3.3)*
Institutions				
Strikes τ	0.168 *(23.3)*	0.157 *(7.4)*	0.132 *(12.4)*	0.008 *(2.4)*
Linear restrictions	Trade=R&D $\phi_2 = \phi_1$ χ^2 (1)=4.494*	Trade=R&D $\phi_2 = \phi_1$ χ^2 (1)=1.843	R&D= Immigrants $\phi_1 = \gamma_2$ χ^2 (1)=16.38**	Females= Immigrants $\gamma_1 = \gamma_2$ χ^2 (1)=0.032

** Significant at the 1 per cent level * Significant at the 5 per cent level
T – ratios are shown in parenthesis calculated by imposing the normality restriction in the β matrix on $\nu(\hat{\varepsilon})_t$ see equation 4.16, Chapter 4.

Figure 7.3 Explaining within-group earnings dispersion in manufacturing

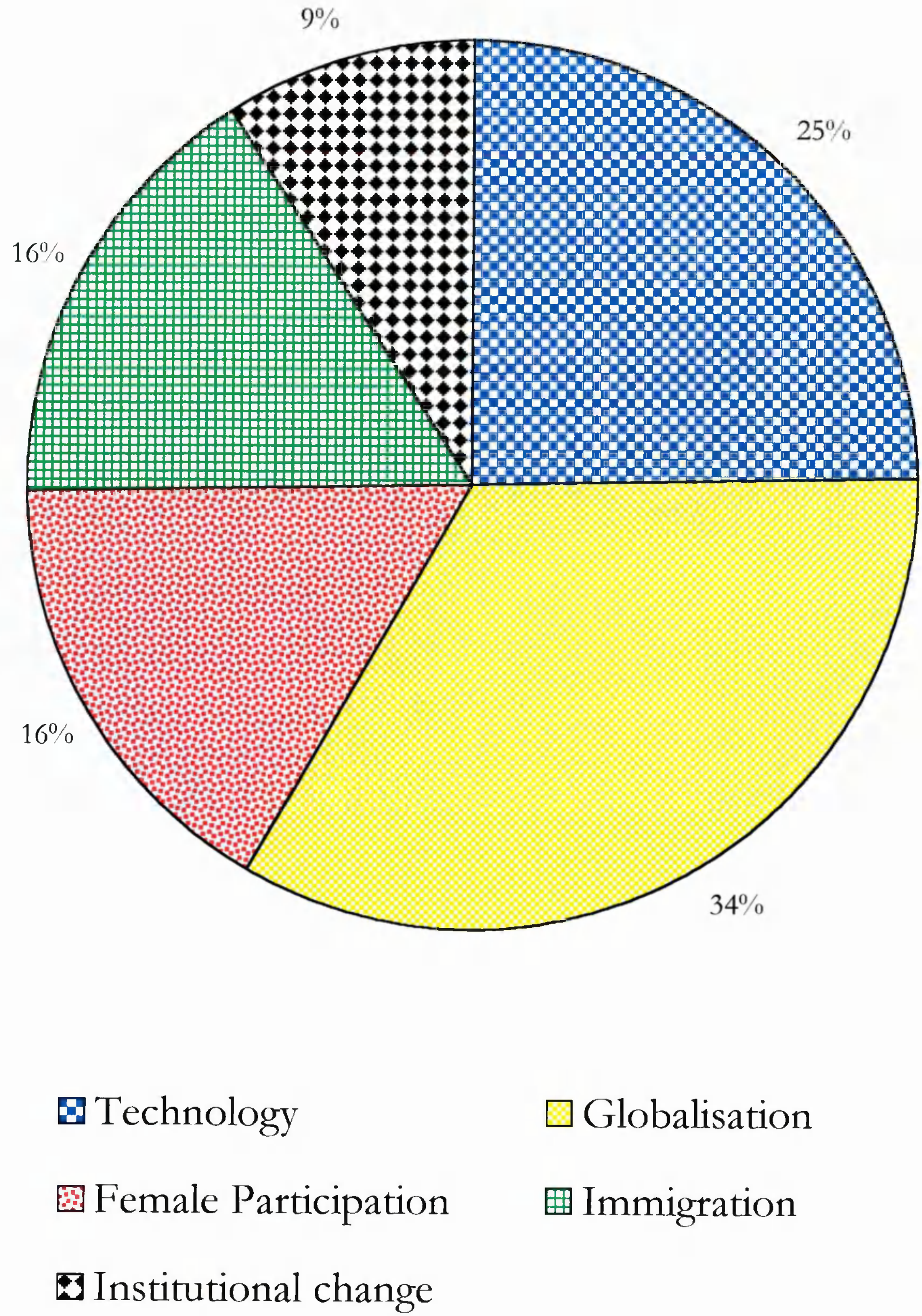


Figure 7.4 Explaining within-group earnings dispersion in other manufacturing

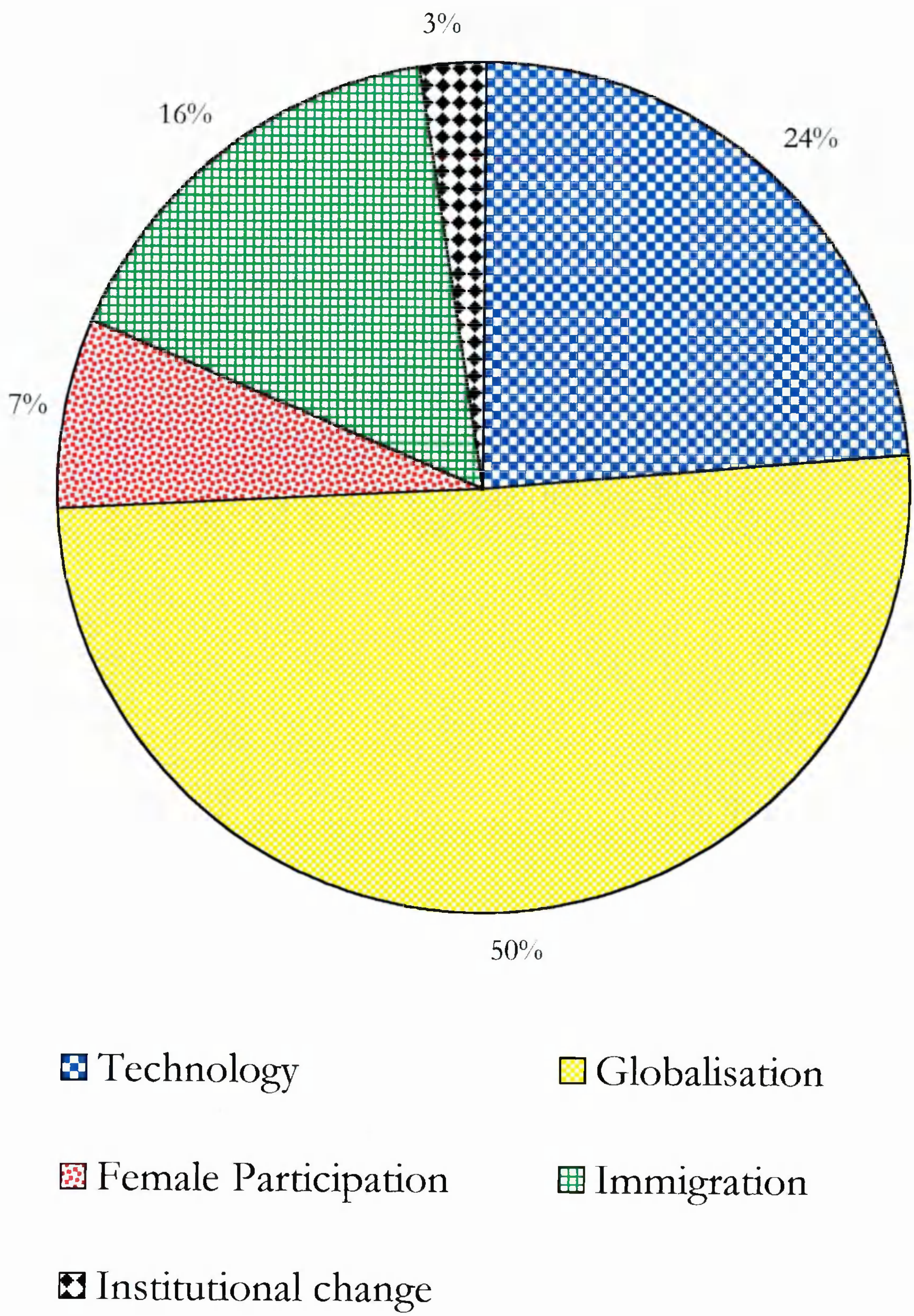


Figure 7.5 Explaining within-group earnings dispersion in construction

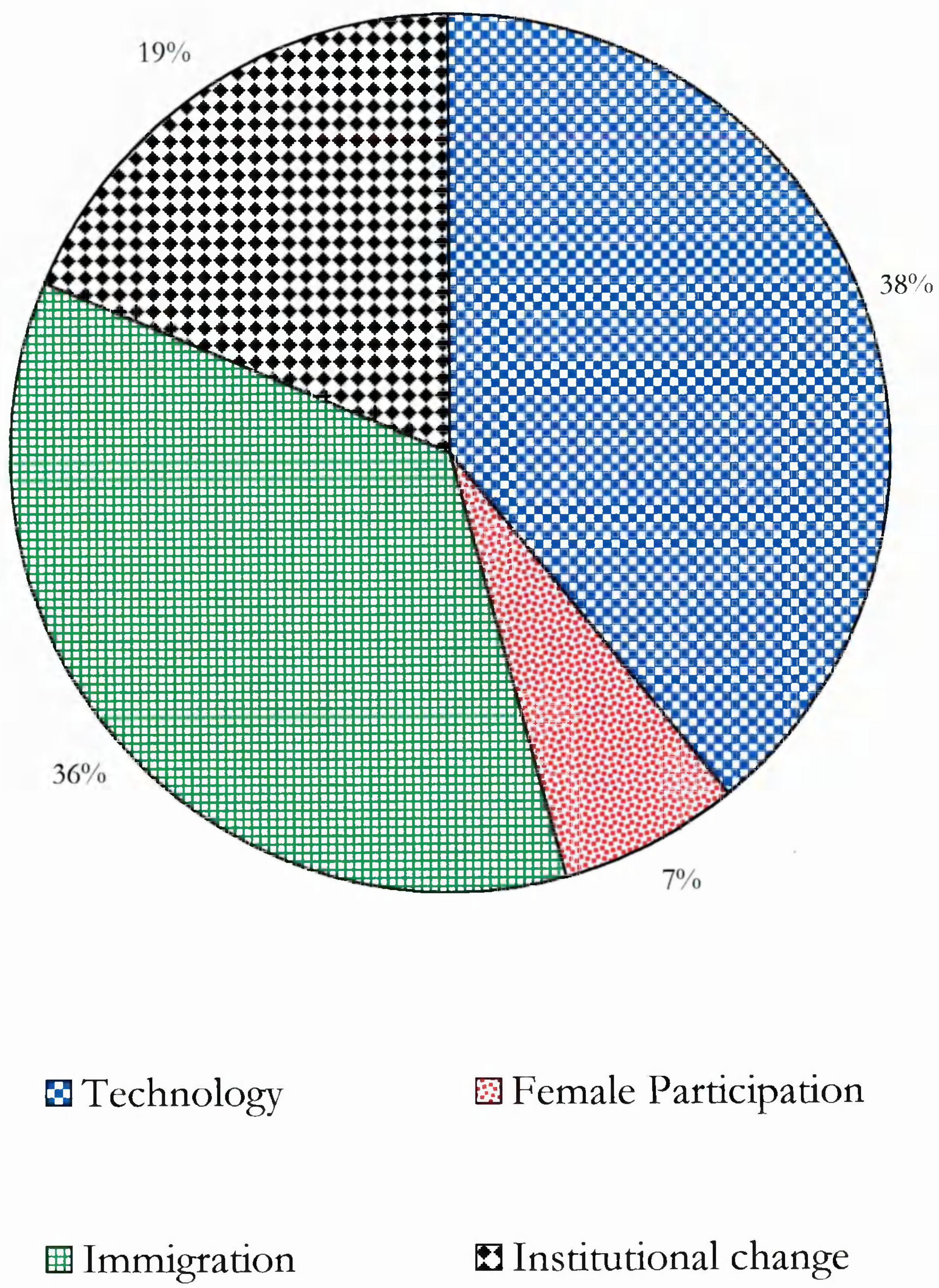
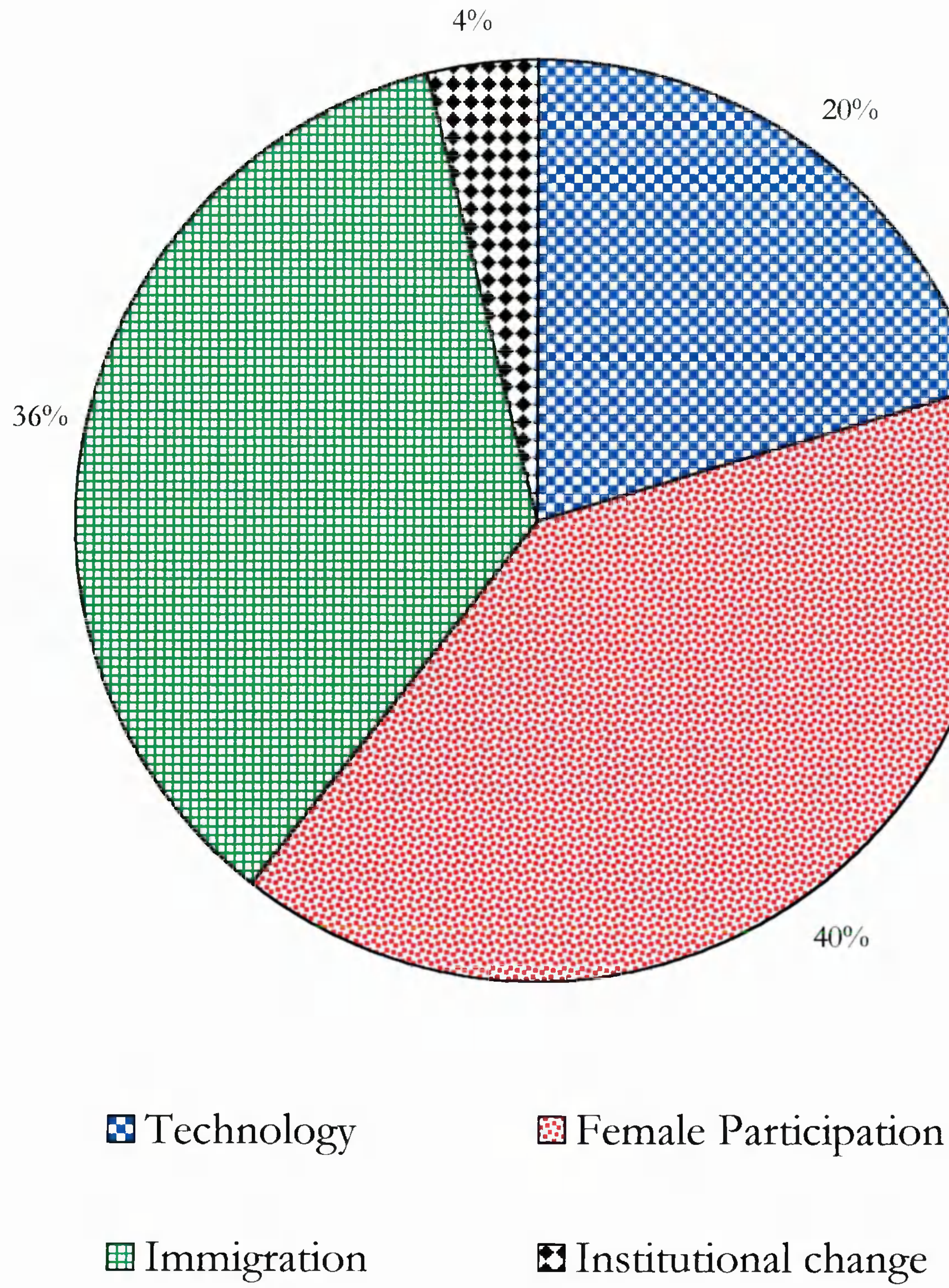


Figure 7.6 Explaining within-group earnings dispersion in transport and communication



The absolute magnitudes of the coefficients are shown as percentages in Figures 7.3 to 7.6, above, for each industry. Clearly, in Manufacturing the coefficient on trade intensity, $\phi_2 = 0.614$, dominates all the others.

A noticeable feature of the results shown in Table 7.7 and Figures 7.3 to 7.6, is that outside of the Construction industry the role of institutional change is relatively small in explaining the variation in within-group earnings dispersion. Moreover, the impact of institutional change can only explain on average 8¾ per cent of the trend in dispersion. This raises the issue of whether strikes are a good measure for the decline in institutional arrangements and in particular collective bargaining. Typically, previous research which has looked at the impact of institutional change upon earnings dispersion has used some measure of unionisation as a proxy for institutional change. Unfortunately, this kind of data was not available at the industry level over such a long period of time - as discussed in Chapter Five. However, a simple plot of the number of workers involved in strikes against union membership revealed a strong correlation (Chapter Five, section 5.3.2, Figure 5.2). The following gives some consideration to the ability of the strike variable to proxy collective bargaining.

The actual development of Britain's collective bargaining system is in large part reflected in the pattern of industrial disputes. An increase in industrial action from the early-mid 1960s[5] reflected the spread of trade unionism and collective bargaining to new groups of employees such as white-collar and public sector workers (Gospel and Palmer, 1993). During the 1970s there was some decline in strike activity in the private sector, which reflected the start of reform and the formalisation of plant and company level bargaining. In the 1980s the number of workers involved in strikes fell and remained on a downward trend into the 1990s[6]. Part of this trend can be explained by changes in labour legislation, making strikes more difficult, but economic and institutional factors have probably been more important in influencing the trend (Brown and Wadhwani, 1991). Consequently, it is likely that the trend in the number of workers involved in strikes proxies the trend in declining collective bargaining fairly well[7,8], as Machin (1997) suggests.

This leads to the question that if the trend in our measure of institutional change follows the same trend as other measures (as footnote 8 suggests) then why is its impact so small in each industry? Previous findings have indicated an impact of institutional change of around 15 to 20 per cent (Gosling and Machin, 1995) yet the largest impact from the cointegration results was 19 per cent in the Construction industry (Table 7.7, Figure 7.5). One possibility is that previous work has typically only tested the impact of institutional

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[5] The number of workers involved in strikes rose from less than 900,000 in the early 1960s to over 2,000,000 by 1968.

[6] Workers involved in strike activity fell from 1,513,000 in 1981 to 176,000 by 1991. Source of figures in footnotes 1 and 2 Department of Employment Gazette for various years.

[7] An alternative to using the number of workers involved in strikes to proxy institutional change is actual data on trade union membership/density for particular unions covering the four industries analysed. However, an attempt to do this by asking specific unions for data revealed very patchy coverage and response.

[8] One check carried out on the adequacy of the strike variable is to compare the percentage decline in the number of workers involved in strikes with data from the Workplace Industrial Relations Survey (WIRS) which showed that collective bargaining declined markedly during the period 1984 to 1990 (Millward, Stevens, Smart and Hawes, 1992). The following table 7.8 compares WIRS data on the change in collective bargaining and union membership between 1984 -1990 to the number of workers involved in strikes. Clearly, each have shown the same trend over the period with similar orders of magnitude between the WIRS collective bargaining measure and strikes – a difference of 7 percentage points.

Table 7.8 A comparison of measures for institutional change 1984 to 1990

Collective Bargaining[a] % change 1984 to 1990	Union membership[b] % change 1984 to 1990	Workers involved in strikes[c] % change 1984 to 1990
-23.94	-17.24	-30.23

[a] Source Millward et al (1992) Table 3.16 All establishments.
[b] Source Millward et al (1992) Table 3.2 All employees.
[c] The 1984 strike figure is a 3 year moving average due to the miners strike of 1984.

change upon dispersion, without including other potential factors such as technological change etc., (for example Leslie and Pu, 1995, 1996) and so consequently this analysis has an advantage in that other factors are controlled for - with the results implying other factors had a larger role to play. Also previous work has typically only taken a snapshot for particular years rather than a long time series, the exception Leslie and Pu (1995, 1996). The following discusses the results found in Table 7.7, followed by an analysis of the impact upon earnings dispersion.

Technological change has a large impact upon within-group earnings dispersion in each industry, never below 20 per cent (Figures 7.3 to 7.6). Yet, it only dominates other explanations in the Construction industry. Outside of Construction the main cause of within-group dispersion is from trade intensity for Manufacturing and Other Manufacturing, and female participation in Transport and Communication. Supply side influences also have a role to play in Construction where immigration can explain 36 per cent of within-group earnings dispersion. These findings are in sharp contrast to existing evidence of the impact of market forces and institutional change on earnings dispersion. It seems that economists are favouring the technological change explanation of causing earnings dispersion or shifts in employment ratios between the skilled to unskilled:

"According to these results, it seems that evidence from the UK and US reaches very similar conclusions. Industries which are more technologically advanced are more likely to have increased their use of relatively skilled workers at a faster rate during the 1980s." [Machin, 1996[a], page 59]

Because the analysis of this study looks at a few industries other than Manufacturing, it seems reasonable that the same factors identified in the literature (Chapter Two and Three) are not causing within-group earnings dispersion across industries. Whilst technological change has a large impact in each sector, other factors have an influence. In particular, trade intensity and supply side influences have a role to play. The results of this study suggest, that further analysis of earnings dispersion is required, but in other industries apart from Manufacturing.

The final row of Table 7.7 reports the results of a test to discover whether there is in fact a statistical difference between the top two factors in influencing within-group earnings dispersion. The results from such a test are shown in the final row of Table 7.7. In the Manufacturing and Construction industries, the hypothesis that the largest impact on within-group earnings dispersion is equal to the second largest factor can be rejected. For Manufacturing, the impact of trade at 34 per cent is found to be statistically different to research and development intensity at 25 per cent $\phi_2 = \phi_1$ gives $\chi^2(1)$=4.49 significant at the 5 per cent level. Likewise in Construction, there is a statistical difference between technology at 38 per cent and immigration at 36 per cent. For the remaining industries the homogeneity restrictions imposed can not be rejected. Whilst trade explains 50 per cent and research and development intensity explains 24 per cent in Other Manufacturing, the two are not statistically different. Rather, the homogeneity restriction $\phi_2 = \phi_1$ gives $\chi^2(1)$=1.84 (Table 7.7, bottom panel). In Transport and Communication, again, the homogeneity restriction that female participation (40 per cent - Figure 7.6) is equal to immigration (36 per cent), $\gamma_1 = \gamma_2$ can not be rejected giving a $\chi^2(1)$=0.03.

This section has attempted to discover the impact of the competing theories upon earnings dispersion. By doing this we have shed light on the role played by market forces and institutional change, something that at the time Machin wrote was unclear:

"What we remain less certain about is the magnitude of the effects attached to each of these factors." [Machin 1996[a], page 63]

The following looks at the direction of the impact each potential cause had on within-group earnings dispersion. By doing this, we can evaluate how the empirical results measure up to the theoretical model (Chapter Two, section 2.6) and the impact predicted.

7.4.3 Direction of influence

The cointegrating vector for each industry[9] (from Table 7.7), showing the impact upon within-group earnings dispersion (T-ratios are shown in square brackets – see Table 7.7) is shown below.

Manufacturing (SIC3)

$$\nu(\hat{\varepsilon})_3 = \underset{[3.2]}{0.452}(TC)_3 - \underset{[-8.2]}{0.614}(G)_3 - \underset{[-4.1]}{0.299}(FP)_3 + \underset{[6.4]}{0.291}(IM)_3 + \underset{[23.3]}{0.168}(IC)_3$$

Other Manufacturing (SIC4)

$$\nu(\hat{\varepsilon})_4 = \underset{[5.5]}{1.429}(TC)_4 + \underset{[9.4]}{3.045}(G)_4 - \underset{[-2.2]}{0.439}(FP)_4 + \underset{[7.0]}{0.958}(IM)_4 - \underset{[-7.4]}{0.157}(IC)_4$$

---

[9] β is the cointegrating vector $\{1\phi_1\phi_2\gamma_1\gamma_2\tau\}$, so for each industry $\forall j$ within-group earnings dispersion is defined by :
$\nu(\hat{\varepsilon})_j = \phi_1(TC)_j + \phi_2(G)_j + \gamma_1(FP)_j + \gamma_2(IM)_j + \tau(IC)_j$
In Construction (SIC5) and Transport and Communication (SIC7), $\phi_2 = 0$.

Construction (SIC5)

$$v(\hat{\varepsilon})_5 = 0.279(TC)_5 - 0.047(FP)_5 - 0.252(IM)_5 + 0.132(IC)_5$$
$$[4.4] \qquad [-0.9] \qquad [-6.9] \qquad [12.4]$$

Transport and Communication (SIC7)

$$v(\hat{\varepsilon})_7 = -0.041(TC)_7 - 0.079(FP)_7 - 0.071(IM)_7 + 0.008(IC)_7$$
$$[-2.9] \qquad [-2.9] \qquad [-3.3] \qquad [2.4]$$

Both Manufacturing and Other Manufacturing experienced an increase in research and development intensity during the 1980s. Consequently, from the cointegrating vector shown above, skill-biased technological change appears to be occurring in both industries as a positive coefficient is found, 0.412 and 1.429 respectively, causing[10] increasing within-group earnings dispersion, which backs up the *prima facie* evidence for Manufacturing from the cross plot shown in Figure 7.1. In the Construction industry the finding of a positive coefficient from the cointegrating vector of 0.279 would imply that technology is low-skill biased, given that research and development intensity fell post 1986. That is as research intensity fell if skill-biased we would expect earnings dispersion to fall – yet this did not occur. This is supported by the finding of a negative correlation between within-group earnings dispersion and technology shown in Figure 7.2, above, where lower research and development intensity is associated with higher within-group earnings dispersion. For Transport and Communication, technology has a negative impact upon dispersion. This suggests the possibility of skill-biased technological change since research and development intensity actually fell in Transport and Communication from 7.4 per cent in 1986 to 6 per

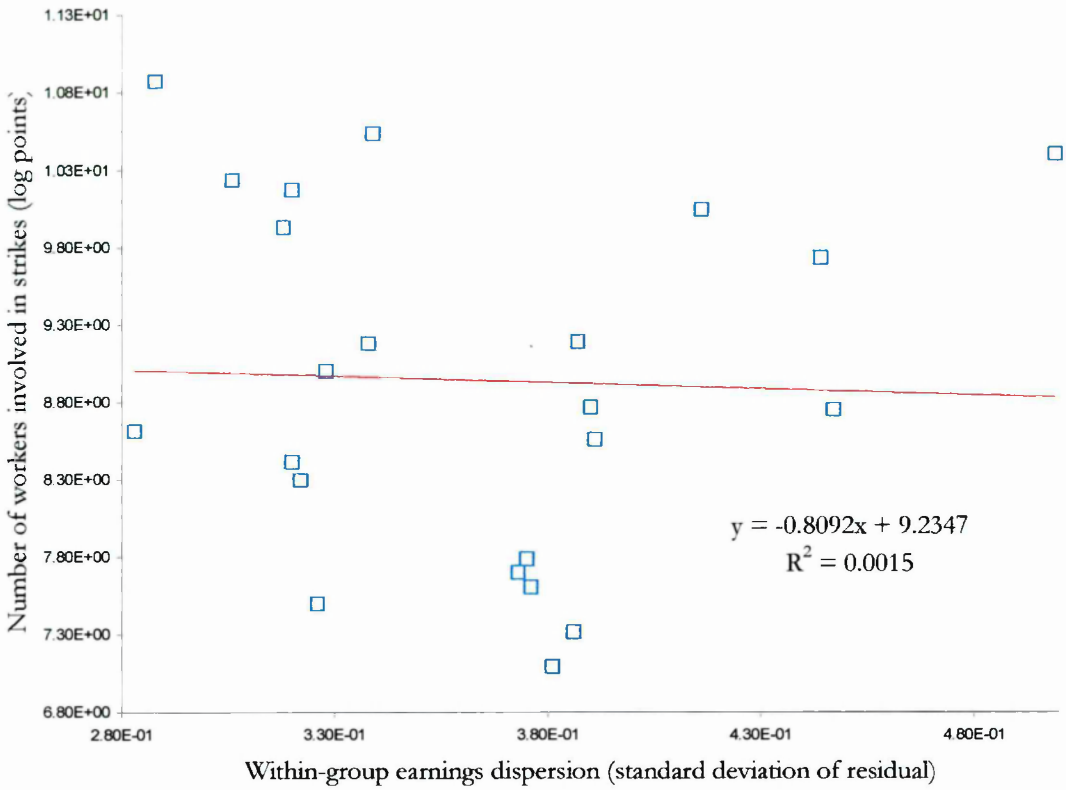
[10] We are able to talk about causation rather than correlation because of the earlier results from the Granger causality tests.

cent by 1992 – a period when within-group earnings dispersion increased substantially (Chapter Six, Figure 6.4).

The theoretical model developed in Chapter Two showed that technological change resulted in increasing dispersion, which suggests that skills and technology are complementary. The empirical evidence for Construction is at odds with the model, although it is possible to adapt the theory to take account of the possibility for unskilled and technology complementarity, by assuming $\left(\partial\left[\frac{\alpha_s}{\alpha_u}\right] \times \partial\left[\frac{1}{t}\right]\right) \langle 0$ that is, over time the relative productivity level of the skilled to unskilled falls, so dispersion $\left(\frac{W_s}{W_u}\right)$ declines (Chapter Two, section 2.6).

The decrease in collective bargaining in each industry is likely to have resulted in an increase in within-group earnings dispersion. Although the impact appears to be small in each industry with the exception of Construction, as discussed above, the direction of the effect shown in the cointegrating vector is usually of the appropriate sign. That is as worker power falls over time this results in higher earnings dispersion, hence the positive correlation between the strike variable and within-group earnings dispersion. The exception is in Other Manufacturing where the coefficient enters as negative. It is possible that this is driven by the increase in the number of workers involved in strikes in the 1990s, from 1,200 in 1990 to 32,800 by 1995. Consequently, this may have mitigated within-group earnings dispersion giving rise to the negative coefficient. This is supported by the cross plot of within-group earnings dispersion to strikes, in Figure 7.7 below, where the line of best fit has a negative slope.

Figure 7.7 Cross plot of within-group earnings dispersion and the number of workers involved in strikes



Female participation increased in each industry, see Appendix A2. The negative coefficient found from the cointegrating vector on female participation across industries suggests that an increasing supply has mitigated dispersion. This implies that rather than being complements to skilled labour, females may actually be substitutes, or that they are relatively skilled. Consequently, if we believe females are skilled, then an increase in their supply will result in a larger pool of skilled labour, thus reducing the price of skilled labour. The alternative explanation is that either group may be a substitute for high skill endowed males. Thus as female participation increases over time the demand for skilled males declines. It follows from either explanation that earnings dispersion falls. This is one possible interpretation of the results found, although the former explanation is more appealing and would be consistent with the observed shift towards employing more skilled labour (Chapters Two and Three), and evidence for the USA (Juhn and Kim, 1999) causing its price to fall as female skilled labour enter the market. The theoretical model assumed that supply side influences were either to substitutes for the low skilled, or that their impact was to increase the supply of the lower skilled. Either scenario would result in greater earnings dispersion between the higher- and lower-skilled. The model can take account of the empirical evidence found for the impact of females, by assuming that over time the rate of substitution declines, $\left(\partial\left[\frac{L_s}{L_u}\right]\times\partial\left[\frac{1}{t}\right]\right)\langle 0$ (derived from Chapter Two, equation 2.3).

In Manufacturing and Other Manufacturing immigration enters the cointegrating vector with a positive sign. Immigration rose in both industries over the period, see Appendix A2. This would suggest that immigrants have consequently lowered the wages of low-skilled labour relative to high-skilled labour thus resulting in widening dispersion. However, for Construction and Transport and Communication the impact is negative which suggests that as with female participation the impact of immigrants may be to mitigate earnings dispersion. A cross plot of earnings dispersion and immigration for the Construction industry in Figure 7.8, below, supports this view, since as immigration increases earnings dispersion falls – a slope of –0.64. However, the finding of a negative coefficient in Transport and Communication for immigration is not supported by the cross plot in Figure 7.9, below. As the cross plot is only an indication of the correlation and is bi-variate, it is possible that the immigration variable is interacting with another variable or variables in a mutli-variate manner causing the negative sign.

Figure 7.8 Cross plot of within-group earnings dispersion and immigration - Construction

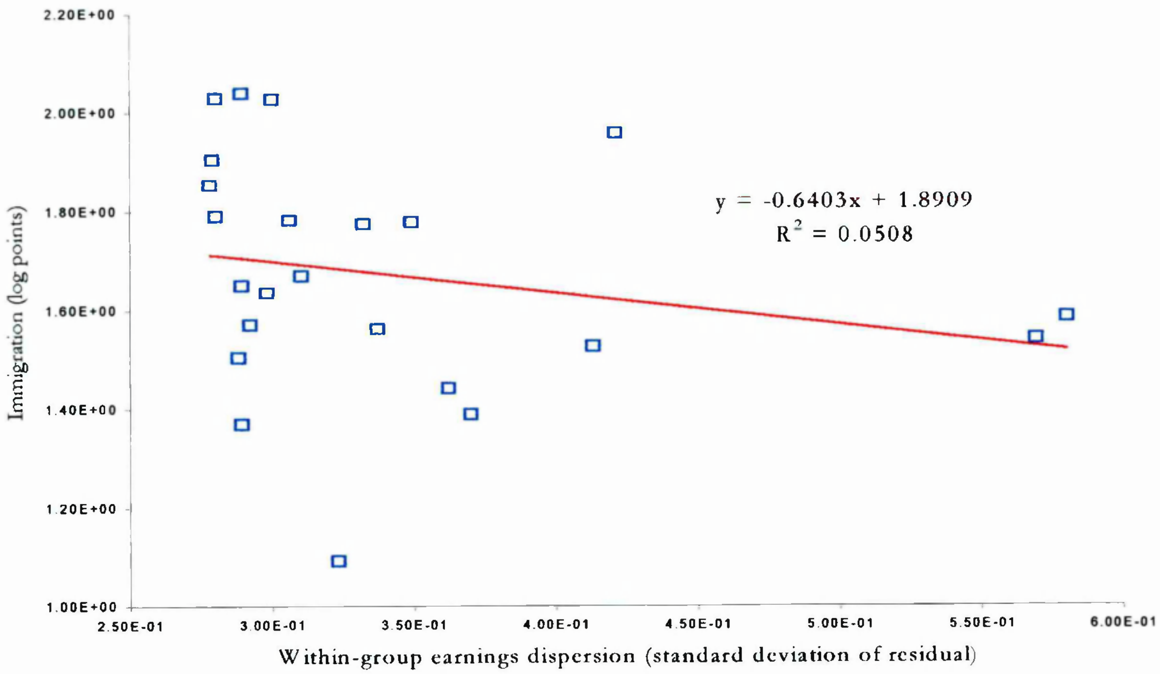
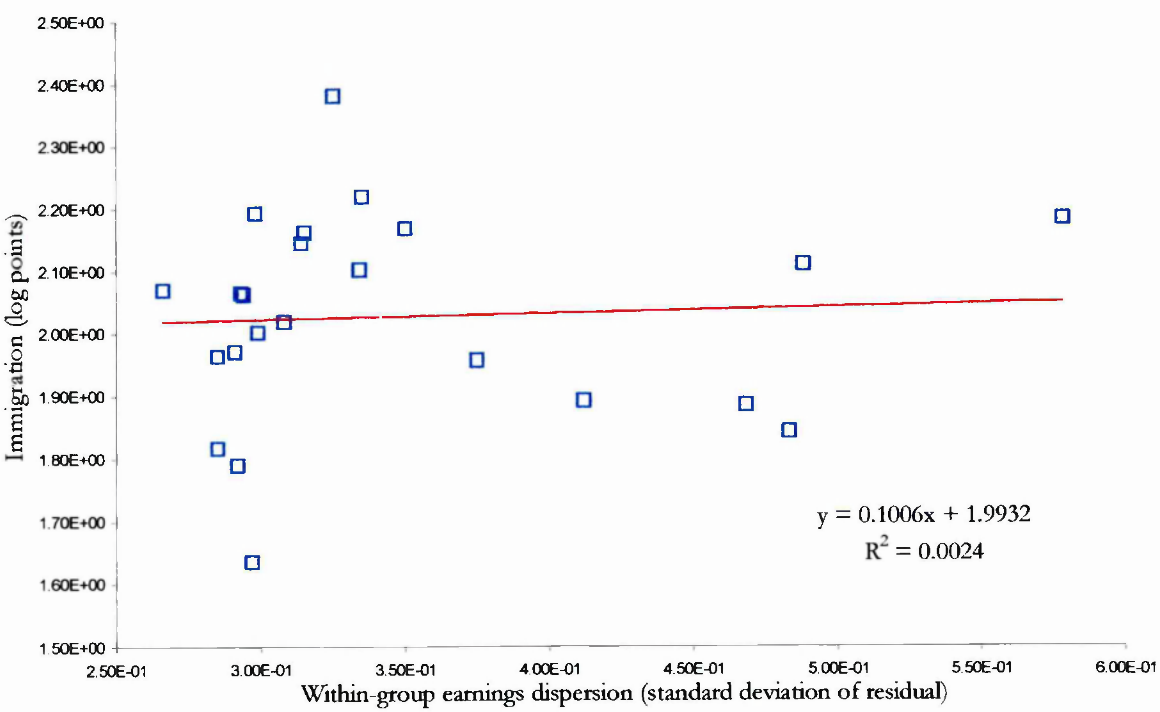


Figure 7.9 Cross plot of within-group earnings dispersion and immigration – Transport and Communication



Noticeably the impact of globalisation is large in both Manufacturing and Other Manufacturing, explaining 34 per cent and 50 per cent of the trend in within-group earnings dispersion respectively. Also the direction of impact is as expected, with increasing trade intensity causing greater within-group earnings dispersion. This is supported by cross plots of trade intensity against earnings dispersion in Figures 7.10 and 7.11, below. In both instances there is a positive correlation.

Figure 7.10 Cross plot of within-group earnings dispersion and trade intensity - Manufacturing

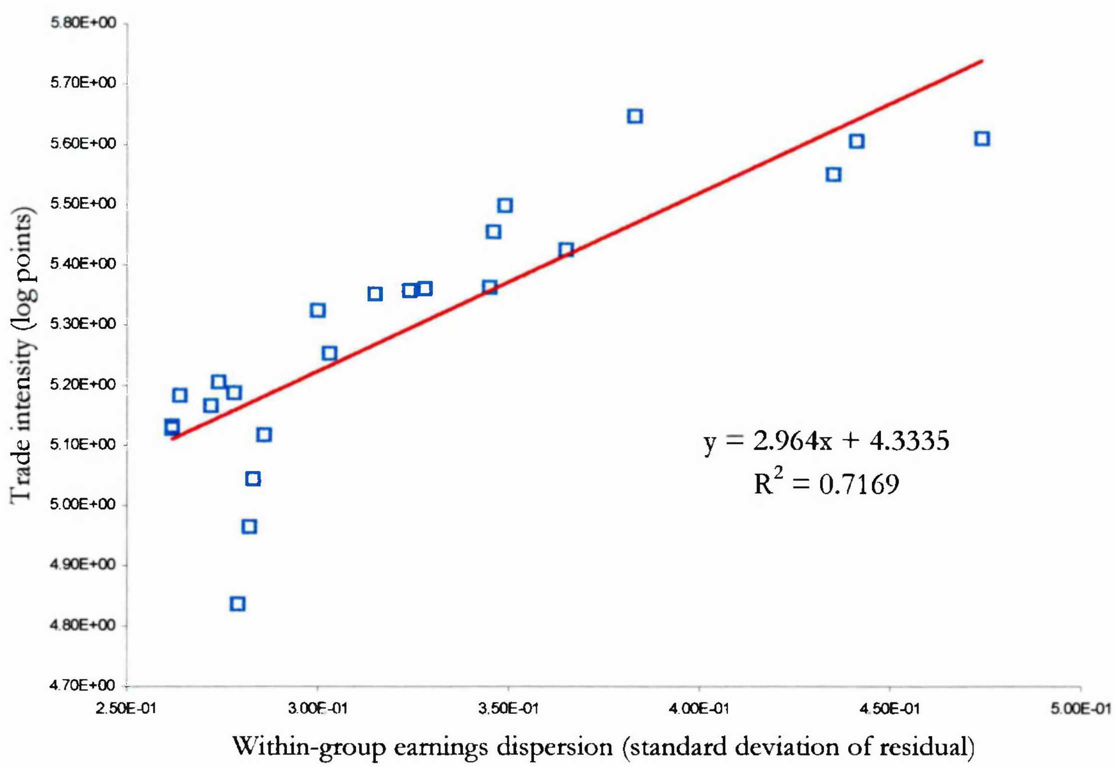
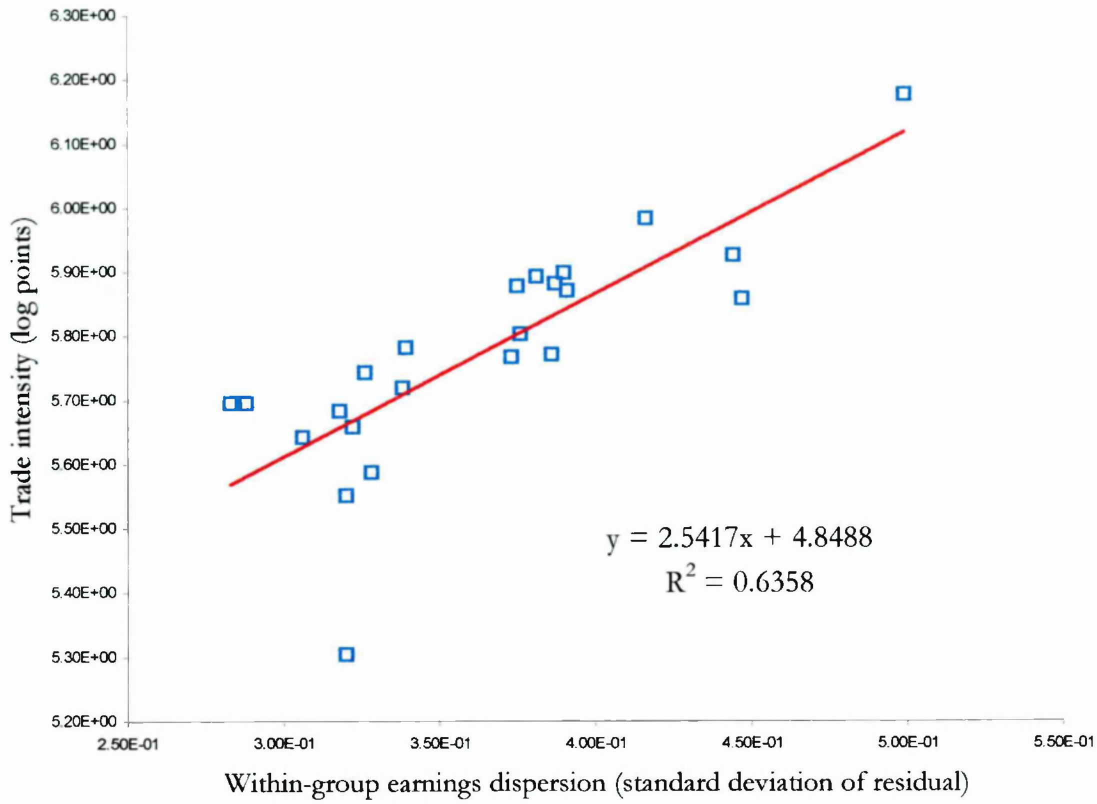


Figure 7.11 Cross plot of within-group earnings dispersion and trade intensity – Other Manufacturing



However, the measure of globalisation used (Chapter Five, section 5.3.1) may be considered weak. In particular, the trade intensity measure is prone to the problems discussed in Chapter Three section 3.2.1 - trade is non-competing (Wood, 1994) and standard measures of trade may be an underestimate (Feenstra and Hanson, 1996). Although the trade intensity measure can be criticised, it is probable that over the 23 years its trend is in the correct direction - imports of manufactured goods rose from £3.4 billion in 1979 to £19.5 billion in 1995 (Hine and Wright, 1998), so the terms of trade index will decline. Wood (1998) has suggested that the majority of the rise in the relative demand for skilled labour during the past two decades was due to skill-biased technological change.

However, what is important is its acceleration over time which Wood (1998) believes to be as a result of globalisation. The cointegration approach adopted to test the competing theories in the second stage should account for this, and be able to consider any change in the trend in globalisation and its impact upon dispersion. Although the analysis is unable to identify when the acceleration occurred, it is evident from Figures 6.1-6.4 (Chapter Six) and Figure A9 (Appendix) that within-group earnings dispersion rose dramatically at the time trade intensity accelerated. Cointegration analysis will account for this due to the fact that the two series move closely together over time and both increase during the 1990s. The fact that the results suggest an average impact of 42 per cent upon the trend in within-group earnings dispersion across both industries implies that part of the relative demand shift was caused by globalisation in the tradeable sector of the economy.

The chapter so far has considered the extent to which the factors identified in the literature review of Chapters Two and Three can influence earnings dispersion once controls have been made for the impact of an individuals characteristics (see Chapter Six). It is also feasible that the factors capable of influencing within-group earnings dispersion may also be effecting the returns to workers characteristics. This is investigated empirically in the next section.

7.5 An analysis of between-group earnings dispersion

To unravel the impact of market forces and institutional changes upon the return to worker characteristics two types of analysis are employed. Initially in sub-section 7.5.1 below the time series methods adopted to discover what drove the trend in within-group earnings dispersion are also applied to between-group earnings dispersion – that is cointegration analysis is used. To see how the returns to education are effected particularly by trade and technology, the industry and individual level data are pooled and the indicators of trade and technology interacted with education levels (sub-section 7.5.2).

7.5.1 Cointegration analysis of between-group earnings dispersion

Before cointegration analysis can be used to see whether technology, trade, immigration, female participation or institutional change influence the variance in that part of earnings which could be explained in Chapter Six (defined by equation 4.5 in Chapter Four), the measure of dispersion needs to be tested for unit roots. As earlier, a variety of approaches are used – ADF, KPSS and Johansen tests. The results are shown in Table 7.8, below.

Table 7.8 Unit root tests on between-group earnings dispersion

Industry / Type of test	Between-group earnings dispersion $v(\hat{\omega})_j$ in the jth industy			
	Manufacturing	Other Manufacturing	Construction	Transport & Communication
ADF levels	2.695 ∴ not I(0)	1.549 ∴ not I(0)	2.286 ∴ not I(0)	1.558 ∴ not I(0)
ADF first difference	6.879** ~ I(1)	8.774** ~ I(1)	6.142** ~ I(1)	5.665** ~ I(1)
KPSS	0.2435**	0.3988**	0.1939*	0.1476*
Johansen	58.289**	47.113**	34.077**	29.464**
Q test	1.459	0.204	0.012	0.696

** Significant at the 1 per cent level * Significant at the 5 per cent level

Table 7.9 Bi-variate cointegration tests

Industry, Variable	*Bi-variate cointegration Engle- Granger two step approach.*
Manufacturing	
R&D intensity	6.18** ~ I(0)
Strikes	5.39** ~ I(0)
Trade intensity	3.71* ~ I(0)
Female participation	6.24** ~ I(0)
Immigration	6.29** ~ I(0)
Other Manufacturing	
R&D intensity	5.69** ~ I(0)
Strikes	5.73** ~ I(0)
Trade intensity	5.58** ~ I(0)
Female participation	4.51** ~ I(0)
Immigration	4.84** ~ I(0)
Construction	
R&D intensity	4.64** ~ I(0)
Strikes	3.97** ~ I(0)
Female participation	4.55** ~ I(0)
Immigration	5.94** ~ I(0)
Transport & Communication	
R&D intensity	5.08** ~ I(0)
Strikes	5.05** ~ I(0)
Female participation	5.61** ~ I(0)
Immigration	5.42** ~ I(0)

** Significant at the 1 per cent level * Significant at the 5 per cent level

The type of unit root test is given down the left hand column and is applied in each industry, shown in the columns, to the measure of between-group dispersion. From Table 7.8, above, the ADF test in levels shows each measure to be non stationary. Furthermore, ADF tests on first differences indicate the data to be I(1), that is stationary after first differencing.

The problems associated with the ADF test were discussed above, in section 7.3, and so KPSS tests are also performed, based upon equations 7.2 to 7.6 above, where the null hypothesis is reversed to stationary data and the method holds well for small samples. Again the results indicate that the data are non-stationary. The same can be seen in the penultimate row by using the multi-variate Johansen test for stationarity, based upon equation 7.1 above. Each of the tests show that at the 1 per cent level between-group earnings dispersion is non-stationary in each industry, usually at the 1 per cent level. The final row of Table 7.8 shows the Ljung-Box Q test as a check to see if a lag length of one year is enough to enduce white noise, see equations 7.7 and 7.8 above. Again a lag of a single year is enough to satisfy the condition for unit root testing in that the residual is a white noise process.

Having found between-group earnings dispersion to be non-stationary Table 7.9, above, shows the results of bi-variate cointegration using the Engle-Granger two stage procedure (see Chapter Four) between the inequality measure and each industry variable. At the 5 per cent level each market force and institutional change variable can be seen to cointegrate in a bi-variate manner with between-group earnings dispersion. Consequently, it is now possible to test for a multi-variate relationship between the industry proxies and between-group earnings dispersion. Table 7.10 gives the results of the number of cointegrating relationships found, based upon Johansen (1988), introduced in Chapter Four, section 4.4. Cointegration rank is tested in Table 7.10, based upon equations 4.14 and 4.15 in Chapter Four. Both the Trace statistic (derived from equation 4.14) and the maximal eigenvalue test (based upon equation 4.15) are significant at the 5 per cent level in each industry. Tests for a rank higher than one are firmly rejected by both the test statistics in each industry and so there is one cointegrating relationship.

Table 7.10 Tests of cointegrating rank adjusted for sample size

Industry	$H_0 : r = 0$ no cointegration $H_1 : r \leq 1$ cointegration, rank less than/equal to one		$H_0 : r = 1$ cointegration rank equal to one $H_1 : r \leq 2$ cointegration, rank less than/equal to two	
	$\lambda_{Trace[T-nk]}$	$\lambda_{Max[T-nk]}$	$\lambda_{Trace[T-nk]}$	$\lambda_{Max[T-nk]}$
Manufacturing	98.76*	46.84**	51.92	27.5
Other Manufacturing	96.95*	41.45*	55.5	27.36
Construction	57.78*	40.12*	56.78	24.04
Transport & Communication	88.29**	40.77*	47.53	20.7

Significant at the *5 per cent level, **1 per cent level, based upon distributions from Osterwald-Lenum (1992).

Figures 7.12 to 7.15, below, compare the absolute size of the cointegrating vector found when between-group earnings dispersion is used as the measure of inequality against the results from within-group earnings dispersion (based upon section 7.4, above). From Figures 7.12 and 7.13 we can see that trade has a larger impact upon between-group earnings dispersion than within-group earnings dispersion. The same is also true for the impact of technology, with the exception of the Construction industry, Figure 7.14, where within-group earnings dispersion is effected to a greater extent. It is also evident from Figures 7.14 and 7.15 that controlling for worker characteristics influences the ranking of the impact. For instance, in the Construction industry, technology has the largest impact upon within-group earnings dispersion, but immigration has the largest impact upon between-group earnings dispersion.

Figure 7.12 The impact of market forces and institutional change upon between- and within-group earnings dispersion: Manufacturing

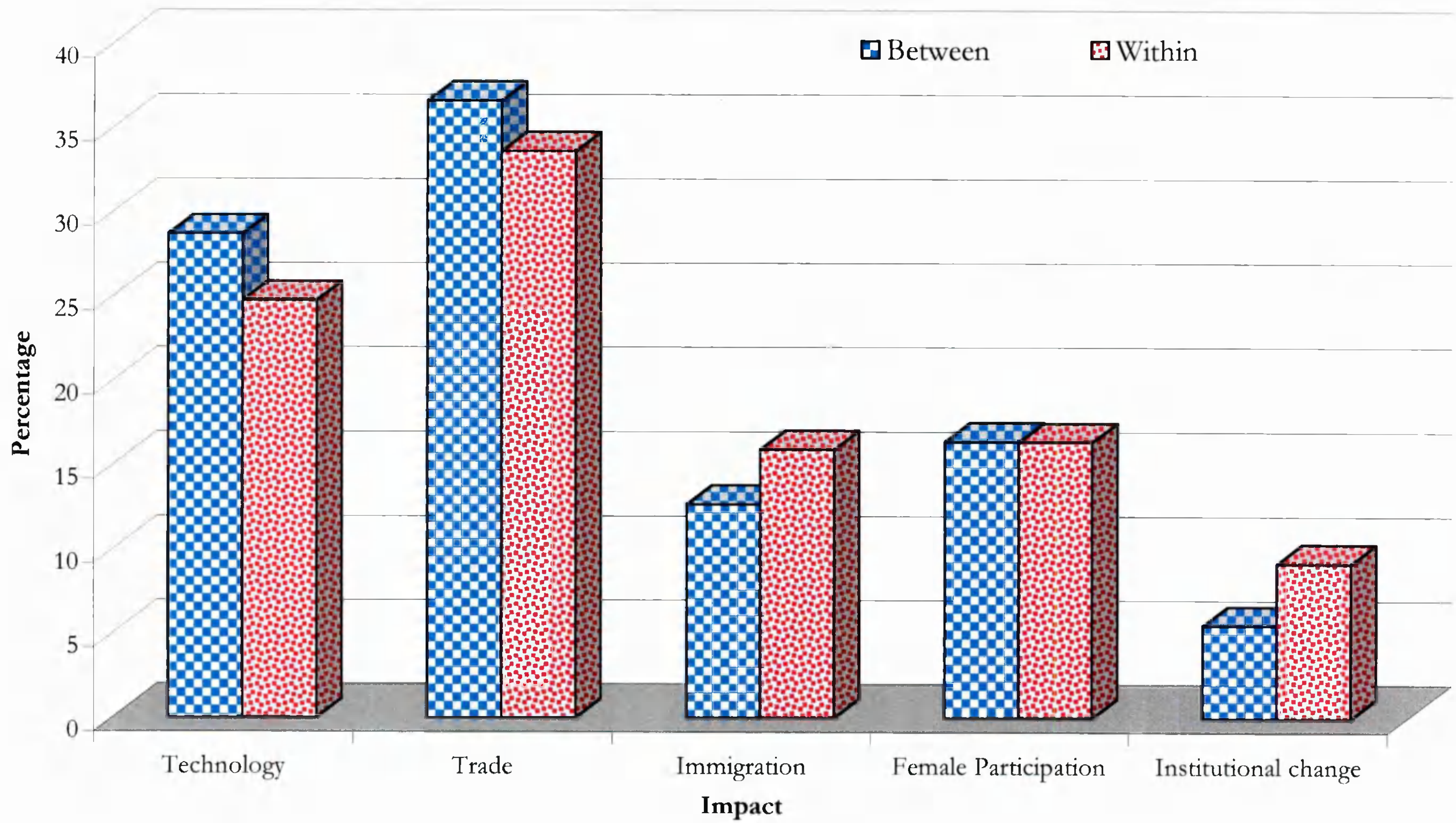


Figure 7.13 The impact of market forces and institutional change upon between- and within-group earnings dispersion: Other Manufacturing

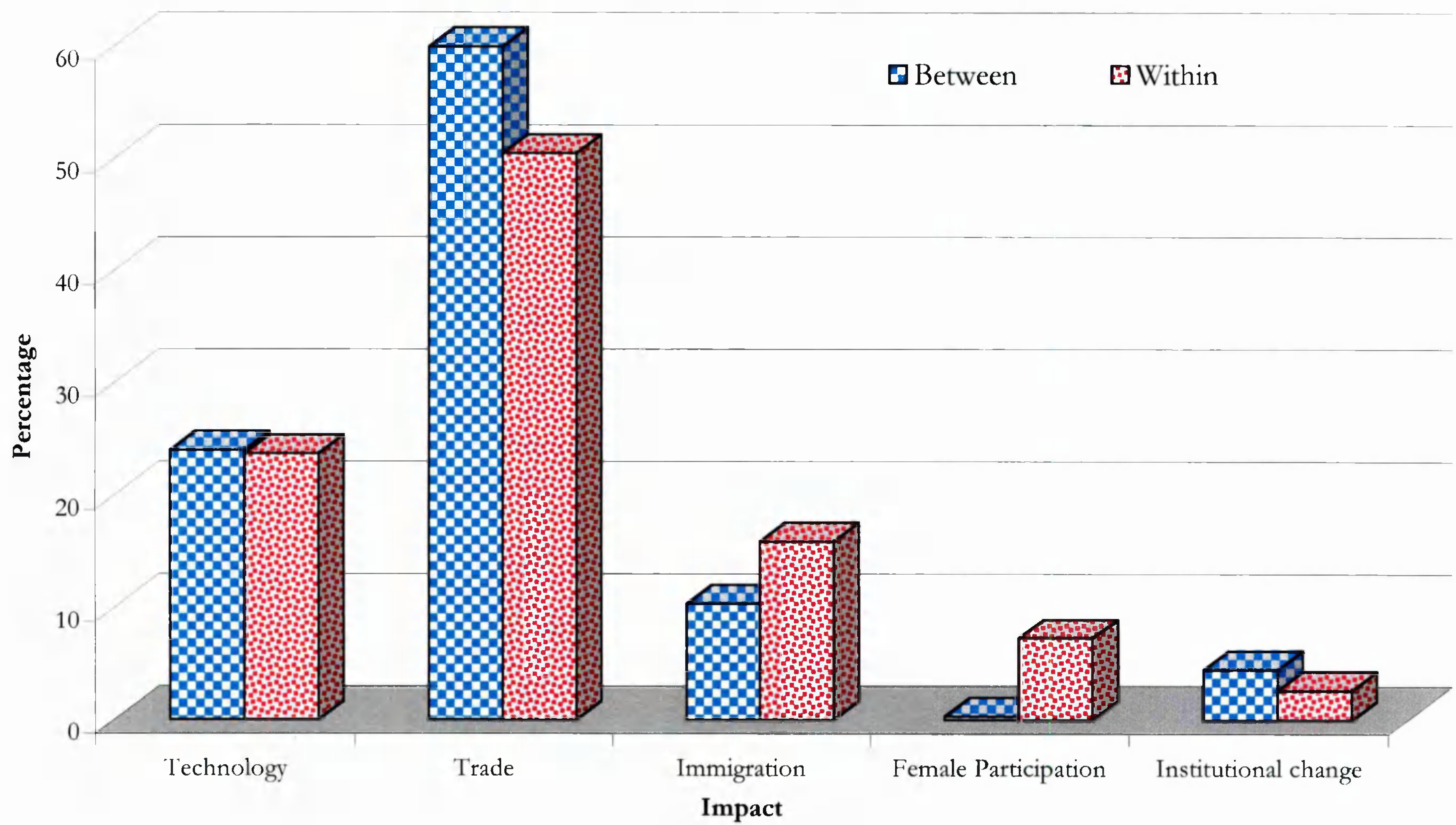


Figure 7.14 The impact of market forces and institutional change upon between- and within-group earnings dispersion: Construction

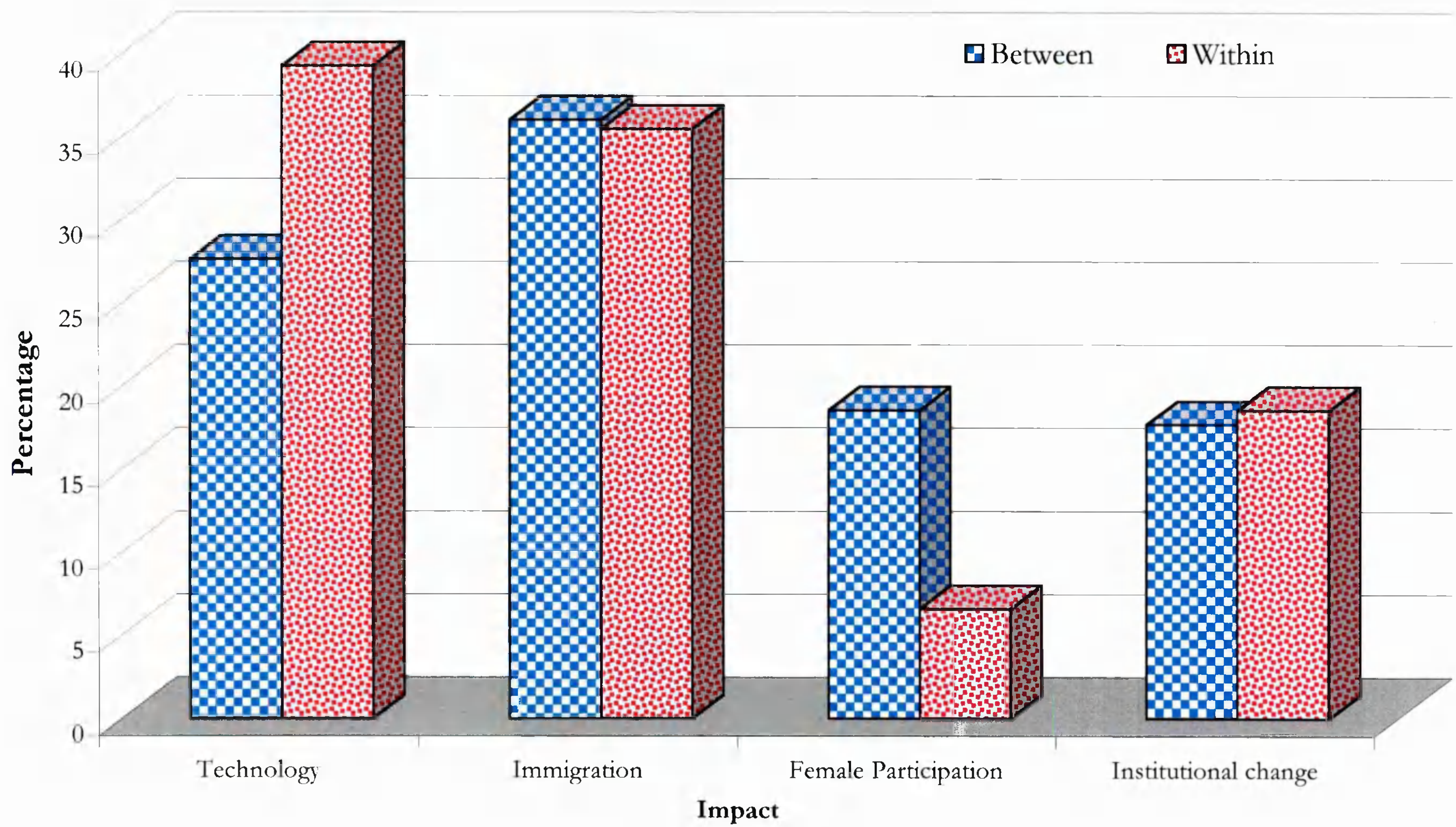
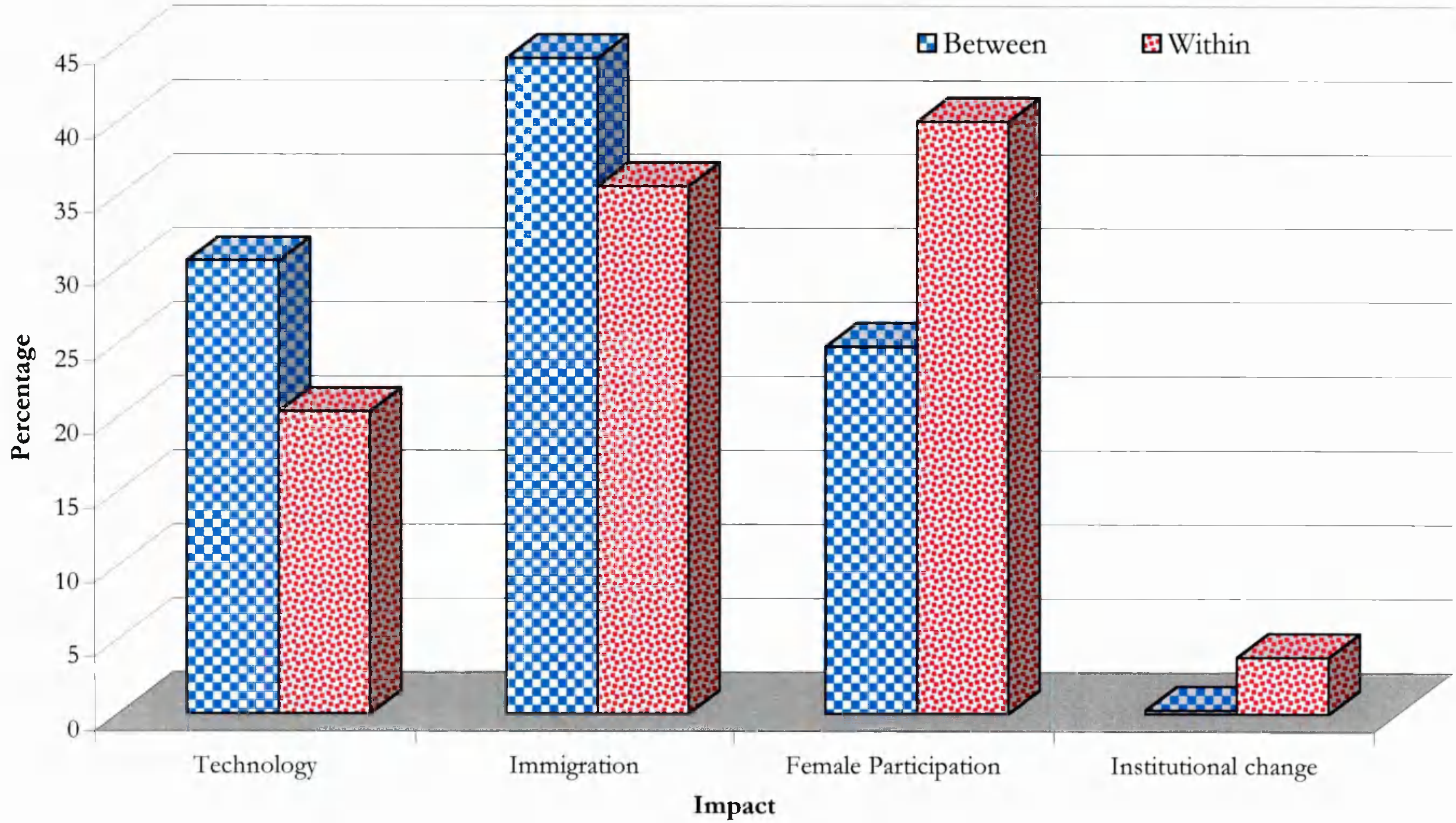


Figure 7.15 The impact of market forces and institutional change upon between- and within-group earnings dispersion: Transport and Communication



Likewise, in Transport and Communication, Figure 7.15, before controls for worker characteristics the largest impact is from immigration, but after employing the methodology used in Chapter Six the greatest impact comes from female participation.

This sub-section has shown that each of the factors identified in the literature (Chapters Two and Three) also have an impact upon between-group earnings dispersion. However, the importance of controlling for individual characteristics and human capital is revealed in Figures 7.12 to 7.15 where the impact upon the explainable and unexplainable part of the earnings distribution differs. Moreover, in Construction and Transport & Communication the ranking of the impacts actually changes. Section 7.5.2 below considers how technology and trade may have influenced the returns to education over time.

7.5.2 The impact of technological change and international trade on the returns to education

The previous section found that both technological change and the growth in international trade played a role in influencing the trend of both between- and within-group earnings dispersion. It is possible that technology and/or trade may also influence the returns to educational characteristics. The dramatic increase in the earnings of more educated workers relative to less educated workers during the 1980s has in previous research been attributed to skill-biased technological change. The nature of the technological revolution meant that labour with higher education endowments witnessed an increase in premiums (Mincer, 1991; Bound and Johnson, 1992; Berman, Bound and Griliches, 1994; Machin; 1996; and Bartel and Sicherman; 1999). Between-group earnings dispersion is influenced by worker characteristics other than just education (see Chapter Six). To focus explicitly on how trade and technology may have influenced the return to education, the following analysis pools the individual level data – used in Chapter Six (to control for observable worker characteristics) – across time and interacts the education dummies with the technology and trade variable, thus

$$Log(\text{Wages})_{it} = X_{it}\delta + \lambda \text{Time}_t + \gamma(E_{it} \times Z_t) + \pi_{it} \qquad \forall j \quad \textbf{(7.13)}$$

$$\pi_{it} \sim \text{IID}(0, \sigma^2)$$

If technology and/or trade has an impact upon the premium associated with education then it should be expected that interactions terms $(E_{it} \times Z_t)$ should be significant and $\gamma \neq 0$. The variables included in the matrix *X* are the same as in Chapter Six and the matrix *Time* introduces a set of year dummies. The results from estimating equation 7.13 in each industry across the period 1973 to 1995 are shown in Tables 7.11 to 7.14, below. Heteroscedastic consistent t-ratios are shown in parenthesis. For Manufacturing and Other Manufacturing the first column of each table shows the impact of technology on education, the second column the impact of trade and the final column the impact of both technology and trade.

The technology and education interactions are each individually significant in Manufacturing, although interestingly the largest returns occur to those individuals who hold an *Apprenticeship* followed by *O Levels*. The results of Chapter Six showed that the return to education rose with educational attainment, yet once interacted with technology this relationship disappears. Technology effects the return to each qualification in a positive manner. A joint test of the significance of the interactions is significant at the 1 per cent level i.e. a test statistic of 99.325 is greater than the table value of $\chi^2(1) = 6.63$. The impact of the trade interactions is similar to that of technology, where the monotonic relationship between higher educational attainment and greater returns disappears. Moreover, the largest impact is for individuals whose highest educational qualification is an *O Level* where the trade interaction actually yields a negative effect.

Table 7.11 The impact of technology and trade upon education: Manufacturing

	Technology Interactions		Trade Interactions		Technology and Trade Interactions	
Degree×Technology	0.5055	*(2.19)*			0.5328	*(2.29)*
Vocational higher× Technology	0.3085	*(1.76)*			0.3236	*(1.78)*
A level× Technology	0.5211	*(3.48)*			0.6142	*(4.08)*
O level× Technology	1.0757	*(7.38)*			0.9744	*(6.62)*
Apprentice× Technology	1.2302	*(9.72)*			1.2182	*(9.69)*
Other× Technology	0.6588	*(3.22)*			0.7084	*(3.43)*
Degree× Trade			0.0541	*(0.66)*	0.0544	*(0.66)*
Vocational higher× Trade			0.0403	*(0.59)*	0.0308	*(0.44)*
A level× Trade			0.1231	*(1.98)*	0.1338	*(2.12)*
O level× Trade			-0.1577	*(2.88)*	-0.1109	*(2.01)*
Apprentice× Trade			-0.0291	*(0.40)*	-0.0212	*(0.29)*
Other× Trade			0.1135	*(1.45)*	0.1171	*(1.46)*
Statistics						
$\bar{R}^2$	0.3560		0.3491		0.3565	
Significance of interactions	99.325		0.432		101.752	
Observations			13112			

Table 7.12 The impact of technology and trade upon education: Other Manufacturing

	Technology Interactions		Trade Interactions		Technology and Trade Interactions	
Degree× Technology	-0.0132	*(0.04)*			0.3644	*(0.99)*
Vocational higher× Technology	0.5041	*(2.20)*			0.8831	*(3.19)*
A level× Technology	-0.1911	*(0.94)*			0.3928	*(1.52)*
O level× Technology	-0.0683	*(0.42)*			0.4718	*(2.25)*
Apprentice× Technology	-0.3239	*(1.91)*			-0.0261	*(0.12)*
Other× Technology	-0.2331	*(1.07)*			0.4568	*(1.53)*
Degree× Trade			-0.5172	*(1.56)*	-0.7528	*(1.86)*
Vocational higher× Trade			-0.2111	*(0.73)*	-0.8352	*(2.39)*
A level× Trade			-0.7647	*(3.56)*	-1.0201	*(3.73)*
O level× Trade			-0.5823	*(3.59)*	-0.8781	*(4.20)*
Apprentice× Trade			-0.4802	*(2.96)*	-0.4535	*(2.10)*
Other× Trade			-0.6867	*(3.35)*	-0.9787	*(3.47)*
Statistics						
$\bar{R}^2$	0.3352		0.3379		0.3391	
Significance of interactions	0.3443		29.208		13.325	
Observations			7970			

Table 7.13 The impact of technology upon education: Construction

	Technology Interactions	
Degree×Technology	-0.2865	*(1.83)*
Vocational higher× Technology	-0.0496	*(0.38)*
A level× Technology	0.2612	*(2.15)*
O level× Technology	0.3027	*(2.62)*
Apprentice× Technology	-0.0798	*(0.70)*
Other× Technology	-0.2327	*(1.24)*
Statistics		
$\overline{R}^2$	0.2479	
Significance of interactions	0.0505	
Observations	6832	

That is increased international trade is associated with a negative impact upon the return to having *O Levels*. A joint test of the significance of the trade and education interactions is insignificant, reflecting the fact that the interaction is insignificant for the highest two educational groups. The final column of Table 7.11 shows the results of including both technology and trade interactions. A joint test is significant at the 1 per cent level, and 8 of the 12 interactions are individually significant. In Manufacturing technology has a positive impact upon returns to education as does international trade with the exception of *O Levels*. To the extent that education reflects an individuals skill the finding of a positive technology-education interaction can be interpreted as skill-technology bias. From the results of section 7.4 not only is technology biased towards those with higher educational qualifications (although not necessarily monotonically), it also favours unobservable skills – that is a positive correlation from the cointegration results of within-group earnings dispersion and technology.

Table 7.14 The impact of technology upon education:

Transport and Communication

	Technology Interactions	
Degree×Technology	-0.2135	*(1.66)*
Vocational higher× Technology	-0.0672	*(0.77)*
A level× Technology	-0.1823	*(1.98)*
O level× Technology	-0.0181	*(0.29)*
Apprentice× Technology	0.1371	*(1.32)*
Other× Technology	-0.0834	*(0.91)*
Statistics		
$\overline{R}^2$	0.3016	
Significance of interactions	2.9246	
Observations	6573	

In Table 7.12 the results are shown for Other Manufacturing. The technology-education interactions are only significant in two out of six instances and a joint test of the significance of the interactions cannot reject the hypothesis of insignificance. In addition, the impact of technology is a negative one for *Apprenticeships*. This suggests the possibility of a low-skill technology relationship – in contrast to the results in section 7.4 where technology was positively correlated with within-group earnings dispersion. However, the negative interaction disappears when trade-education interactions are added to the specification as shown in the final column of Table 7.12. The inclusion of trade effects makes a joint test of the coefficients significantly different from zero at the 1 per cent level. Interestingly, the trade-education interactions are negative when both included individually and with technology. This implies that more highly educated workers were adversely affected by international trade – and is at odds with the findings of the impact of trade upon unobservable skills.

In both Construction and Transport & Communication – the non tradeable sectors of the economy – only the technology indicator is interacted with educational attainment. For the Construction industry the measure of technology actually declined over the period, that is research and development intensity fell. The technology-education interaction is only significant in three out of six instances and a joint test across education groups is insignificant. In two of the cases, the finding of a positive coefficient suggests low-skill technology bias (since technology actually fell) and is consistent with the evidence in section 7.4 once controls have been made for observable skills. That is, in the Construction industry for both observable and unobservable skills the relationship with technology was one of low-skill technology bias. In Transport and Communication the technology-education interaction is significant in two out of the six instances and a joint test is significant at the 10 per cent level. The impact of technology is a negative one and since research and development intensity fell in this industry implies a skill-biased technology association – consistent with the evidence above in section 7.4.

Both section 7.5.1 and 7.5.2 have shown that the industry level explanations of earnings dispersion have had an impact upon the trend in earnings dispersion which could be explained by individual characteristics, and have also influenced the returns to education.

7.6 Conclusion

The results presented in this chapter have attempted to explain earnings dispersion over nearly a quarter of a century. What the results have shown is that the same influences upon within-group earnings dispersion are not important in each industry. In particular, only in the Construction industry does technological change dominate other explanations – international trade and supply side factors are found to be of greater importance in other industries.

The chapter also considered how market forces and institutional changes may have influenced between-group earnings dispersion, finding that there were different impacts upon between- and within-group earnings dispersion. The impact of technology and/or trade upon the return to education was also investigated, where generally a significant relationship between the technology and/or trade interactions with education was found, although the effects were not always biased towards higher educational attainment.

The existing evidence to date on earnings dispersion in the United Kingdom has either been based upon economy level analysis (Schmitt, 1995; Leslie and Pu, 1995, 1996) or upon a number of manufacturing industries (Machin, 1996[a,b]). The results of this study imply that further analysis of earnings dispersion, preferably considering industries other than Manufacturing, should be undertaken. Detailed diagnostic tests have revealed that the cointegration model is well specified and exhibits no empirical problems in terms of diagnostics.

8

Conclusion

8.1 Introduction

The aim of this chapter is to provide a summary of the thesis in section 8.2 along with any policy implications, and in section 8.3 to suggest directions for future research. Section 8.2 firstly identifies the key themes in the literature able to explain both between- and within-group earnings dispersion and the problems faced previously in empirical modelling. The two stage empirical procedure adopted in the light of an absence of suitable panel data is outlined along with the empirical results from each stage. Finally, section 8.3 considers the avenues of possible future research such as assessing the impacts of unobserved ability and possible interactions between the influences on within-group earnings dispersion identified.

8.2 An overview of the thesis

Chapter Two introduced the main themes in the literature which are capable of explaining within-group earnings dispersion. In particular these were identified as skill biased technological change, globalisation, female participation, immigration and declining collective bargaining. The skill biased technological change hypothesis suggests that technological advances over recent years, such as the introduction of the micro computer, have favoured more highly skilled workers. Moreover, demand has shifted in favour of more highly skill endowed individuals resulting in increased earnings dispersion. The impact of globalisation has also had a similar impact upon demand. Over time the number of UK firms producing low skill intensive goods has fallen as a result of lower wages abroad - in particular the Far East - due to outsourcing, causing the relative wages of the skilled to unskilled to diverge.

Both female participation and immigration have also been identified in the literature as possible causes of within-group earnings dispersion. If either groups are substitutes to low skill endowed labour then a rise in supply will result in a fall in the demand for the low skilled. Conversely, it may be that both females and immigrants are on average lower skilled than those low skilled workers already in the labour market are. Under such a scenario rising supply of females/immigrants will lead to an increase in the supply of unskilled labour, thus depressing its price and so increasing dispersion.

Whilst technological change, globalisation, female participation and immigration are market force explanations for within-group earnings dispersion, Chapter Two also identified influences aside from market force explanations, the importance of labour market institutions and how they have evolved - in particular the role of trade unions and their ability to reduce wage disparities.

The dominate theme in the literature is that the demand for skilled labour has increased over time at a rate faster than for lesser skilled individuals. Whilst each of the above factors are able to explain this demand shift, it is possible that influences upon earnings dispersion can occur that are not reflected in the competitive labour market. Such influences are discussed in Chapter Two and are given as organisational change incorporating efficiency wages and insider-outsider effects. Whilst these factors can also explain earnings dispersion and may indeed become more important in the future, the remainder of the thesis focused upon testing the competitive demand and supply framework for explaining earnings dispersion since this is the dominate paradigm in the literature.

The factors identified in Chapter Two have been empirically tested previously and Chapter Three reviewed the empirical approaches used to analyse how each influenced earnings dispersion. In particular, it has been common to use earnings functions to control for the impact of an individuals characteristics upon earnings, thereby decomposing earnings dispersion into between-group and within-group components (Juhn, Murphy and Pierce, 1993). Earnings functions have also been employed to assess the role of technology and unionisation, by including some kind of proxy in the equation (Krueger, 1993; Freeman, 1993). A specific problem identified in Chapter Three of including technology indicators is endogeneity bias, that is does technology cause higher earnings or are those individuals with higher earnings more likely to use new technology (DiNardo and Pischke, 1997). Trends in earnings dispersion over time have also been looked at and compared to the trends in factors capable of explaining dispersion, for example falling unionisation and globalisation (Borjas and Ramey, 1994; Leslie and Pu, 1995, 1996). The modelling framework for this kind of analysis has been cointegration (Johansen, 1988).

From the literature review of Chapter Three a two stage empirical model was formulated in Chapter Four, stemming from techniques grounded in the literature. Specifically by combining two research methods apparent in the literature - cross sectional earnings functions and time series analysis - this study has taken an innovative approach in analysing earnings dispersion over time. In Chapter Four it was argued that a two stage approach was necessary for two reasons. Firstly, by pooling individual level data (used to control for workers' characteristics) and industry level data (used to proxy the themes in the literature) results are likely to contain aggregation bias (Moulton, 1989) where mixing micro data with more aggregated data can result in inflated standard errors and invalid t statistics. Secondly, although it is possible to overcome this by adopting cell means if some of the data is non-stationary then it is possible that any result will be a spurious regression. To gain some insight into how earnings dispersion has changed over time within groups of individuals controlled for the impact of education, experience etc., a two stage approach has been argued to be the best viable option in the absence of panel data. More specifically, in the first stage earnings functions are used to decompose earnings dispersion into between-group and within-group components. In the second step the trend in within-group dispersion is examined over time, and time series techniques are employed to attribute which factor had the largest influence upon earnings dispersion.

The data required for the two empirical stages has been introduced in Chapter Five. Micro economic data was required for the first stage in order to control for worker characteristics and decompose earnings dispersion into between- and within-group components. More aggregated industry data was required in the second stage to proxy the key themes identified in the literature in an attempt to explain within-group earnings dispersion. Using consistent consecutive cross sections of the General Household Survey over the period 1973 to 1995, it is possible to decompose earnings dispersion into between-group and within-group earnings dispersion. Specific problems of data consistency over time were identified as changing definitions in earnings and changing industrial classifications. It was shown that although the definition of earnings changed twice over the period firstly in 1979 and then in 1992 that the earnings data was consistent, following the methodology of Schmitt (1993). Schmitt (1993) showed the earnings data pre- and post-

1979 to be consistent with the New Earnings Survey, by comparing the trend in earnings at the 90th, 50th and 10th percentiles. Using the same method it was shown in Chapter Five that the data pre- and post-1992 was consistent with the New Earnings Survey.

As regards changing industry classifications, the General Household Survey had twenty-four one digit industry codes before 1980 and ten thereafter. There is a possibility that attempting to match the industries over the break period may lead to inconsistencies. In previous work with the General Household Survey Blanchflower and Oswald (1994) used the maximum ten categories, whilst Schmitt (1995) could only match seven. The approach adopted in Chapter Five was to consider the percentage change year on year in the industry size relative to the total sample size, after matching the twenty-four categories down to ten possible groups. Consequently, five industries were found to be consistent following the SIC change in 1980 - Agriculture, Manufacturing, Other Manufacturing, Construction, and Transport and Communication. Agriculture was omitted due to declining sample sizes, which meant that the empirical model could not be estimated, as some of the indicators had no variation.

Chapter Five also introduced the more aggregated industry level data to proxy technological change, globalisation, female participation, immigration and institutional change. Specifically research and development intensity – defined as R&D expenditure in 1973 prices as a proportion of value added in 1973 prices – was used to proxy technological change. Trade intensity was measured by import plus export expenditure in 1973 prices as a proportion of value added in 1973 prices. Both female participation and immigration were proxied by the number of each group employed by industry as a proportion of total sample size, and industrial change was proxied by the number of workers involved in strike activity. Whilst the preferred measure of institutional change would have been some measure of trade union power i.e. density or membership this was unavailable at the industry level on a consistent basis over time. However, in Chapter Five section 5.3 of Chapter Five we saw that the trend in the number of workers involved in strikes is correlated with trade union membership - a correlation coefficient of 0.88. Previous research has also suggested that strike activity proxies trade union membership or density, Machin (1997). Further checks of the adequacy of the strike variable in Chapter Seven section 7.4.2 footnote 8 found that it followed the same trend in the WIRS measure of collective bargaining.

A key aim of this study has been to extend the existing evidence on earnings dispersion by providing evidence over a long period of time in industries other than Manufacturing. Evidence to date for the United Kingdom has only offered snapshots (Schmitt, 1995; and Machin, 1996[a]), rather than forming a consistent time series of within-group earnings dispersion. Chapter Six undertook the first part of this task by decomposing earnings dispersion into between-group and within-group components. As expected overall earnings dispersion rose over the period 1973 to 1995 in each of the four industries. In particular earnings dispersion was found to occur within groups controlled for education, experience and other controls. Such dispersion dominated between-group earnings dispersion and is consistent with previous research findings (Schmitt, 1995; and Machin, 1996[a]). Although an hours variable could not be used in the regression banded hour dummies showed that variations in the hours worked per week did not influence earnings dispersion. The regression method used to decompose earnings into between-group and within-group dispersion was tested for robustness in a number of ways - functional form, heteroscedasticity, outliers, parameter stability and omitted variable bias. The occurrence of any of the above could bias the measure of within-group dispersion needed in the second stage of the analysis. Whilst the functional form was found to fit the data adequately, there was a need to control for heteroscedasticity and outliers. Over the twenty-three years considered in the study 90 per cent of the parameters in each industry were found to be stable, indicating acceptable model specification over the period. The main empirical problem was one of omitted variable bias in some years as indicated by the Hausman test. This means that the measure of within-group dispersion may be biased. However, it should be realised that omitted variable bias is a problem with econometrics in that it is not possible to control for all of the relevant factors which may influence earnings. Bearing this in mind any earnings dispersion remaining after controlling for worker characteristics was explained in Chapter Seven.

A key motivation for this thesis is: what has influenced the trend in within-group earnings dispersion over time? The fact that within-group earnings dispersion dominates between-group earnings dispersion (Chapter Six, Figures 6.1 to 6.4) implies that the demand for skilled workers has outpaced the corresponding changes in supply. In particular, over the period 1980 to 1990 the returns to education *vis á vis* no qualifications increased as did the relative supply of such groups. This indicates that relative demand must have shifted in favour of the higher skilled, otherwise an increase in supply alone would have depressed skill prices – yet this was not witnessed[1].

[1] However, recent research has shown that although following an increase in the relative supply of skills initially the relative price falls, a higher proportion of skilled workers implies a large market size for skill-complementary technologies (Acemoglu, 1998). As a result, an increase in the supply of skills reduces the skill premium in the short run, but then it induces skill-biased technical change and increases the skill premium. This is an important theoretical finding and needs to be empirically tested to find the causal impact upon earnings dispersion. Moreover, did supply changes or technological change cause increasing skill prices?

This interpretation is consistent with what previous researchers have found (Levy and Murnane, 1992; Gottschalk and Smeeding, 1997; Schmitt, 1995; Machin, 1996[a,b], and Machin and Van Reenen, 1998). Having decomposed earnings dispersion into between-group and within-group effects, what remains is to try to determine the cause of within-group earnings dispersion. The second stage of the empirical analysis tested to see what may be responsible for such a demand shift in terms of the key themes identified in Chapter Two.

More precisely, Chapter Seven employed cointegration techniques in order to discover which key theme identified in the literature has the largest influence upon within-group earnings dispersion over time. By considering industries apart from just Manufacturing it is possible that different factors have not had the same impact in each industry. Firstly, a number of empirical tests were carried out checking whether the data had unit roots and if a bi-variate cointegration relationship held between each proxy and within-group earnings dispersion. The results indicated that the data was all non-stationary and so standard estimation based upon OLS could have resulted in a spurious regression. Each proxy was found to cointegrate with within-group earnings dispersion and consequently was entered into a multi-variate model. Granger causality tests showed that causality ran from each possible explanatory factor to within-group earnings dispersion. This would inform us which theme in the literature had the largest impact upon earnings dispersion. One multi-variate cointegrating relationship was found relating within-group earnings dispersion to each possible cause. In particular, it was found that international trade had the largest impact upon within-group earnings dispersion in Manufacturing and Other Manufacturing. However, supply side influences also had a role to play as did technological change – never having an impact less than 24 per cent.

The factors capable of explaining within-group earnings dispersion could also be influencing the trend in between-group earnings dispersion. This was examined by employing cointegration techniques and revealed that the impact of market forces and institutional change differed upon each measure. This means that the factors identified as potentially affecting the within-group variance in Chapter Two were also affecting the between-group variance. Moreover, in some cases the major impact upon between-group earnings dispersion was different to within-group earnings dispersion – that is the ranking of the impact altered for the two wage dispersion measures. To discover how technology and/or trade may have influenced the return to education, the individual and industry level data were pooled over time and technology and/or trade indicators interacted with education dummies. The results showed that both trade and technology influenced the return to education over time, although the impacts differed across industries.

The crucial finding of this study is that industries have been influenced by factors other than technological change. Existing research in Great Britain has only analysed earnings dispersion for the economy as a whole, or Manufacturing only (Schmitt 1995 and Machin 1996[a,b]). Because of this, it may not be surprising that the results of this study, which is an industry level analysis, differ from previous research. What the results of this study suggest is that further analysis of earnings dispersion is required, but in other industries apart from Manufacturing. That is, it is not possible to summarise from Manufacturing what has caused earnings dispersion to increase. In other words, to understand what happened to the economy-wide relative demand for low skilled labour, it is vital to consider industries other than Manufacturing.

Of interest for policy makers is the impact of demand and supply changes upon productivity and inflation (Haskel and Martin, 1996). Demand for skilled workers outpaced corresponding changes in supply (Chapter Six; Levy and Murnane, 1992; Schmitt, 1995; and Machin, 1996[a,b]). In the wake of skill shortages firms will have to wait longer to fill vacancies and this consequently increases their costs. As a result, firms may substitute to lower skilled labour and so productivity declines. Skill shortages also improve the options for those workers with higher skill endowments. This can result in declining effort and so falling levels of productivity. As regards the impact of skill shortages upon inflation, if the supply of skilled workers is insufficient, then firms are likely to concede larger wage increases in order to preserve their base of skill labour - which is inflationary. Also skilled labour is in a stronger bargaining position and so relative wages may widen.

8.3 Directions for future research

Whilst the skill-shift explanation has been cited for causing rising earnings dispersion, it is only part of the story. Another factor, which needs investigating further empirically is the changing nature of firms, where employers now require much more flexibility amongst their employees. Traditional work arrangements, in which employees perform highly specialised, fragmented jobs, are increasingly giving way to ones where a substantial segment of the work force performs several tasks - Multi tasking. Future research should consider how the need for workers to be able to multi task affected the earnings distribution (Lindbeck and Snower, 1996). Early indications from Green (1998) suggest that this may be of importance, where he finds that task variety has a positive and significant impact upon pay. The impact of organisational changes should also be modelled from adopting non-competitive labour market frameworks such as efficiency wages and insider-outsider approaches (Snower, 1998).

Recent research has found that technological change is skill neutral (Nickell and Bell, 1996), or that, after controlling for the potential endogeneity of technological change indicators such as computer usage, the effects are small. It has been argued that technological change can favour the unskilled (Goldin and Katz, 1996), where skill complementarity has changed as the production process altered. In particular, the adoption of new machinery is skill biased, but as assembly line techniques occur, capital becomes a complement to low-skill-endowed labour. In the United Kingdom the evidence of capital-skill complementarity has been associated with the computer revolution and the introduction of the microchip. However, are we now starting to experience a fall in strength of the capital skill complementarity now that assembly line techniques, have taken off such as CNC machining? Only future research using better measures of technological change will reveal the answer to this. Certainly, the evidence presented in this study, suggests that not all industries have experienced skill-biased technological change. This is particularly true of Other Manufacturing and the Construction industry (Chapter Seven)

Finally, there is a possibility that the same factors that produced the increase in demand for skilled labour - market forces, may also have contributed to the decline in collective bargaining as unions began to recognise that wage structures were becoming much more competitive. If this is true, then the decentralisation of wage bargaining is due to these market force changes in a causal sense. Alternatively, decentralisation may allow more wage flexibility in response to changes in demand and supply, and so the causal link is decentralisation to market forces. Future research should attempt to disentangle the potential interactions between competing theories - to find which started the causal chain of events.

Appendix

A1 Available education categories and regional indicators

The final educational groups used in the analysis consists of six categories (Chapter Five, section 5.2.3). These categories are derived from fifteen possible categories reported in the General Household Survey (GHS), as shown in Table A1, below. Owing to the falling sample sizes over the sample period it was not possible to use all of the categories and so six groups were used (Blackaby et al, 1997).

Table A1 Educational categories drawn from the General Household Survey

Qualification	*1973 to 1976*	*1977 to 1982*	*1983 to 1986*	*1987 to 1995*
Higher degree	1	1	1	1
First degree	2	2	2	2
Teaching qualification	3	3	3	3
Vocational higher	4	4	4	4
Nursing qualification	5	5	5	5
A' levels	6	6	6, 7	6, 7
O' Levels 5 or more	7	7	8	8
O' levels less than 4 and clerical qual.	8	8	9	9
O' levels less than 4 no clerical qual.	9	9	10	10
Clerical	10	10	11	11
CSE grades 2 to 5	11	11	12	12
Apprenticeship	12	12	13	13
Foreign qualification	13	13	14	15
Other qualifications	14	14	15	14, 16
No qualifications	0	15	16	17

The GHS regional categories are also fairly consistent over the period 1973 to 1995. Table A2 shows how the regions were matched over time from the GHS coding.

Table A2 Regional categories drawn from the General Household Survey

Region	*1973, 1975 to 1977*	*1974*	*1978 to 1983*	*1984 to 1995*
North	1	1	1	1, 2
York & Humberside	2	2	2	3, 4
North West	3	3	3	5, 6
East Midlands	4	4	4	7
West Midlands	5	5	5	8, 9
East Anglia	6	6	6	10
Greater London	7	7	7	11, 12
South East	8	8	8, 9	13, 14
South West	9	9	10	15
Wales	10	10	11	16, 17
Scotland	11	11, 12	12	18 to 22

A2 Trends in the industry data

Figure A1 Strike activity - Manufacturing and Other Manufacturing

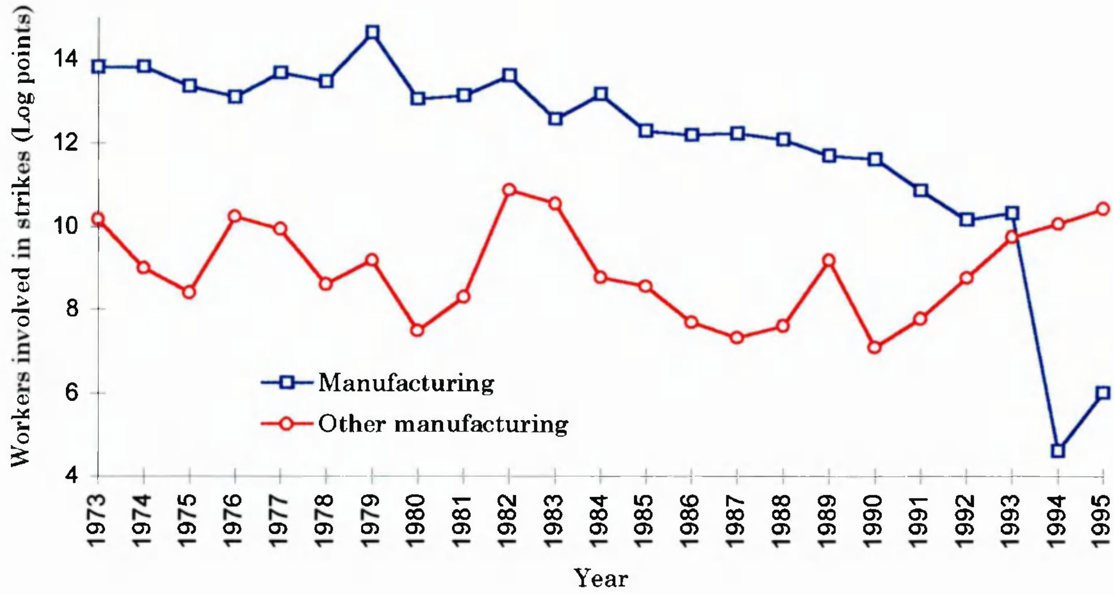


Figure A2 Strike activity - Construction and Transport and Communication.

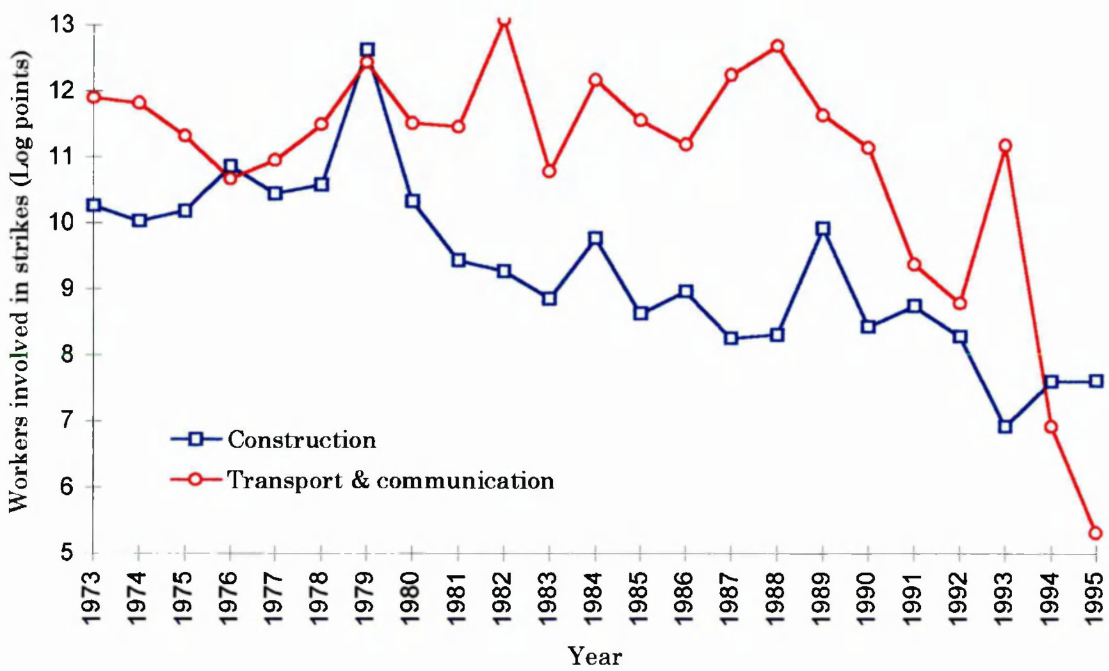


Figure A3 R&D intensity - Manufacturing and Other Manufacturing

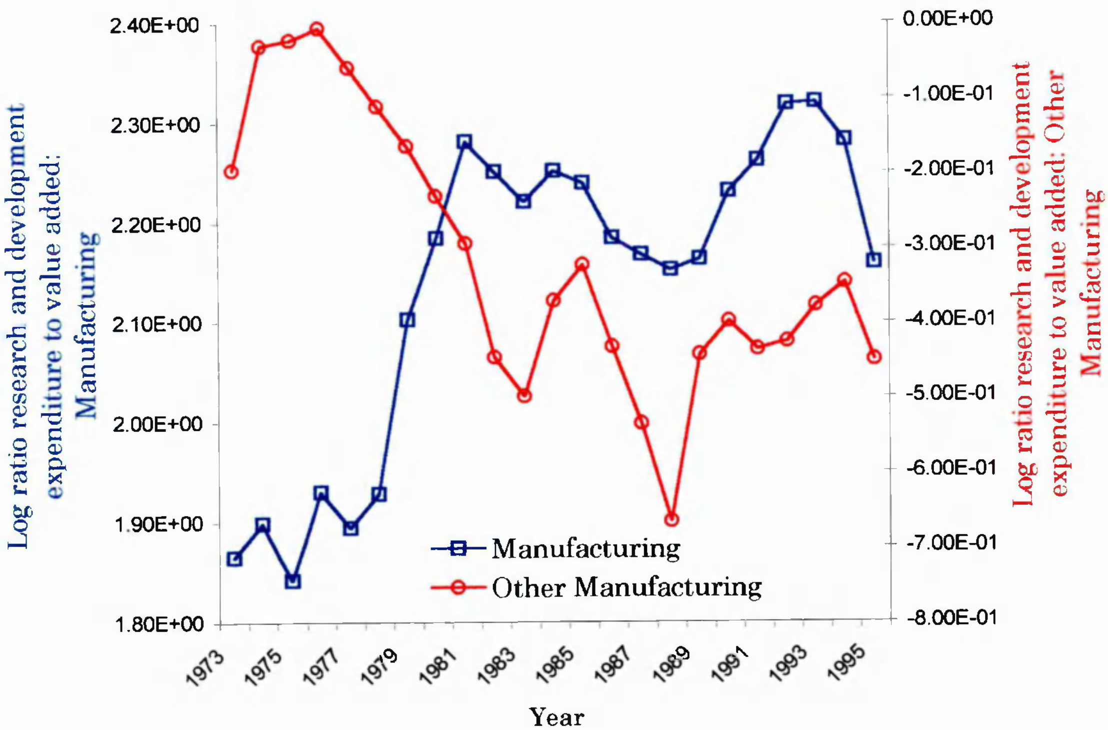


Figure A4 R&D intensity - Construction and Transport and Communication

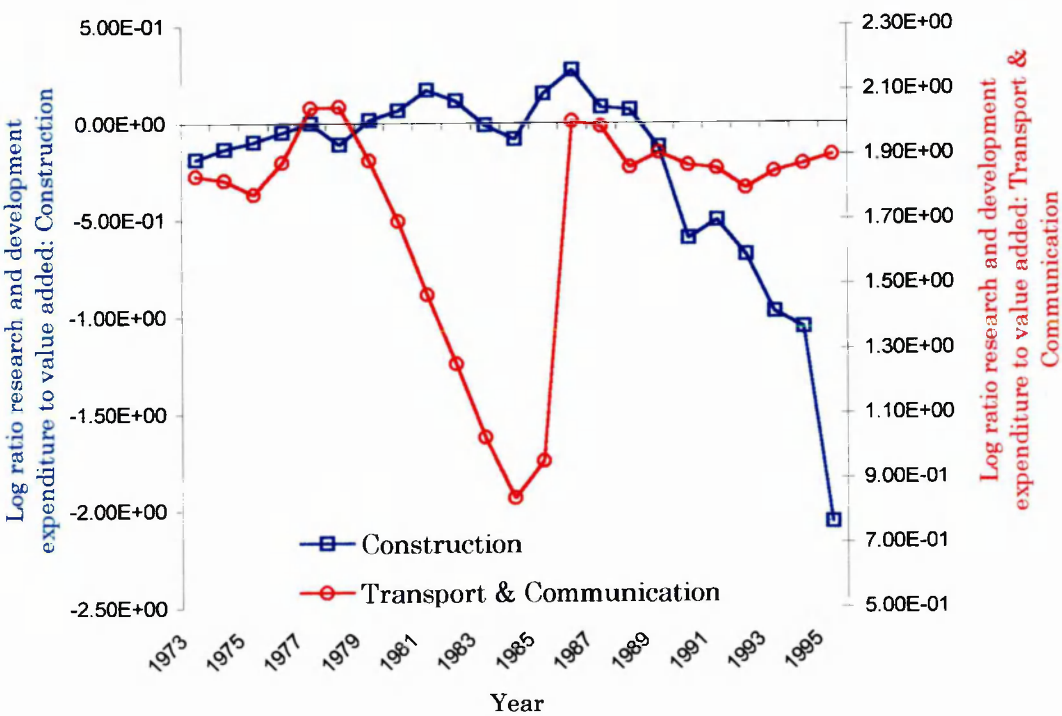


Figure A5 Female participation - Manufacturing and Other Manufacturing

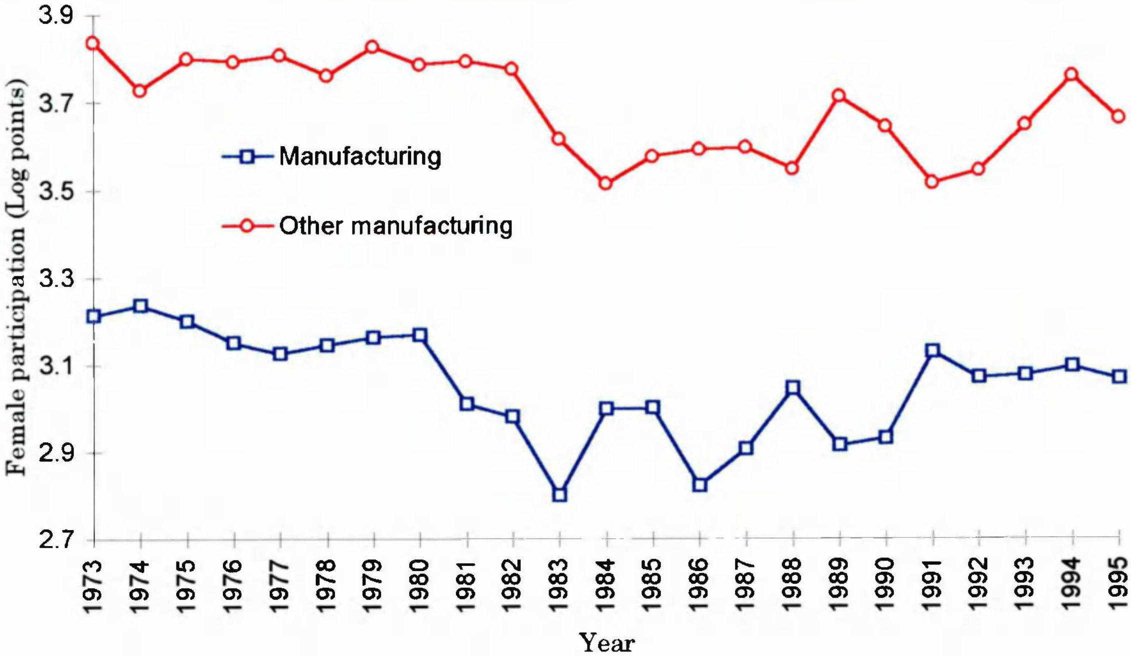


Figure A6 Female participation - Construction and Transport and Communication

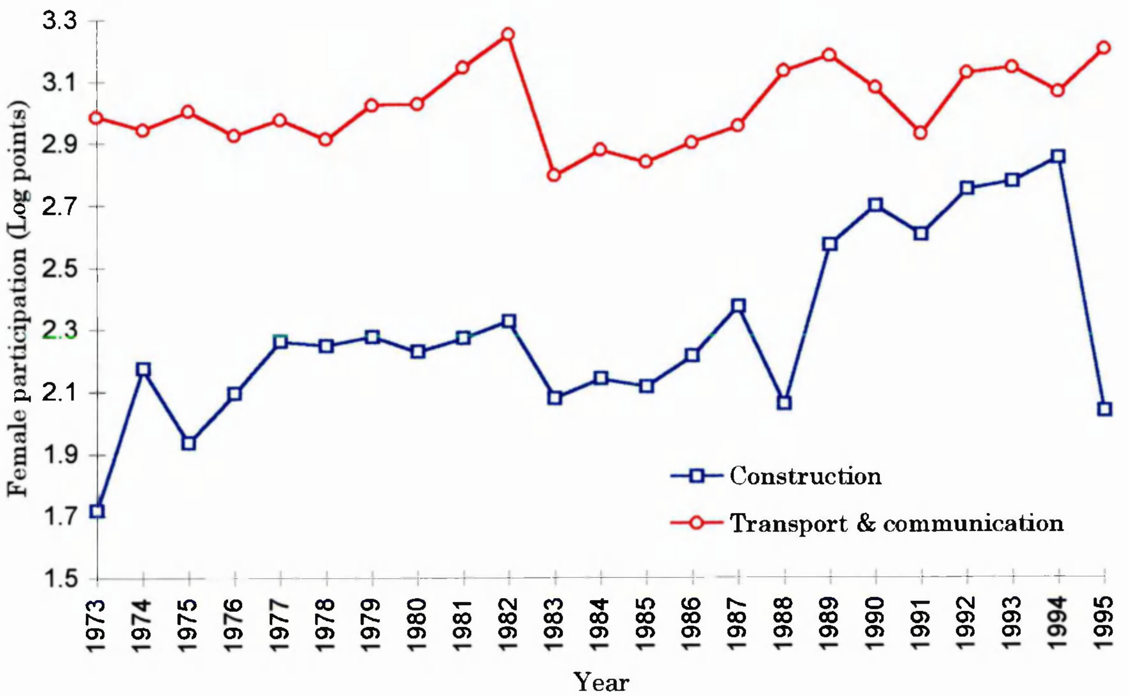


Figure A7 The supply of immigrants - Manufacturing and Other Manufacturing

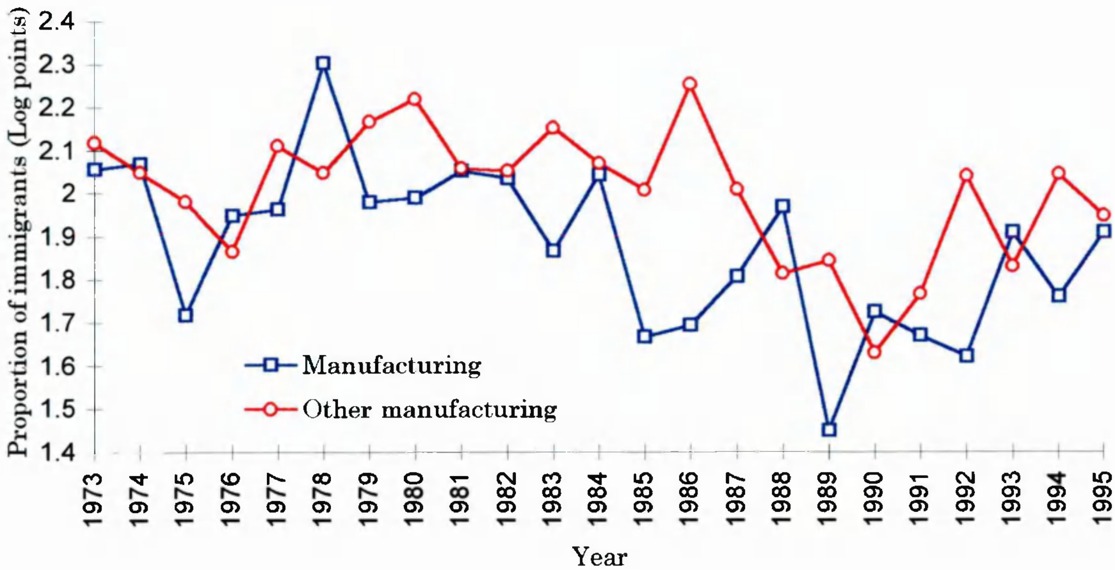


Figure A8 The supply of immigrants - Construction and Transport and Communication

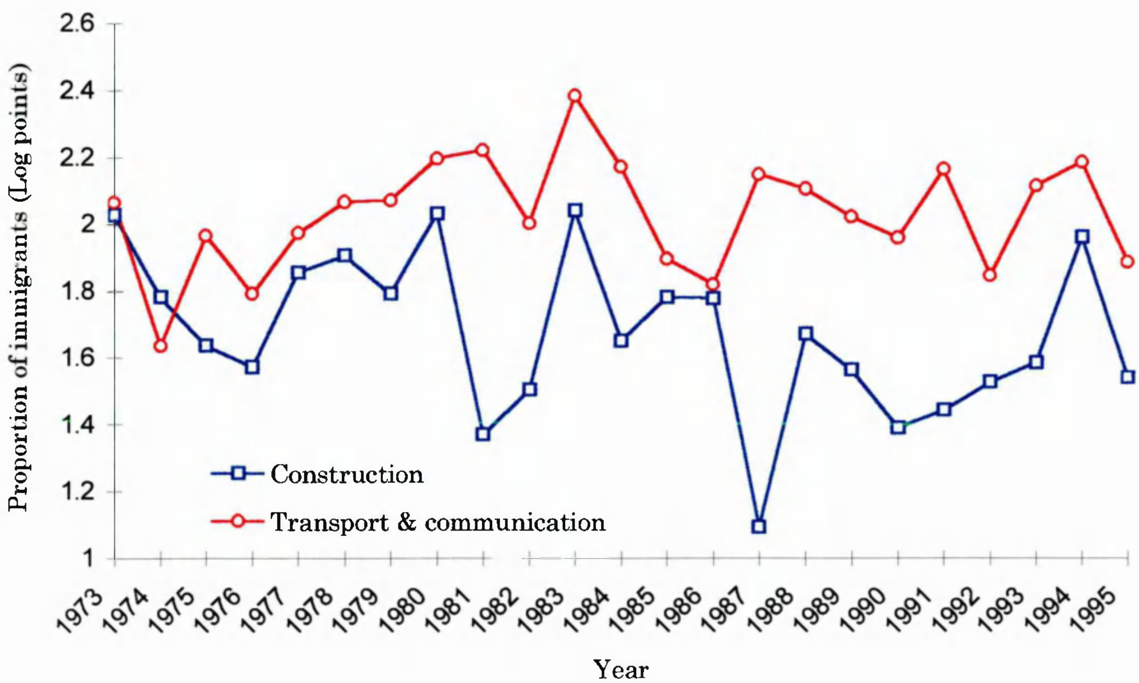
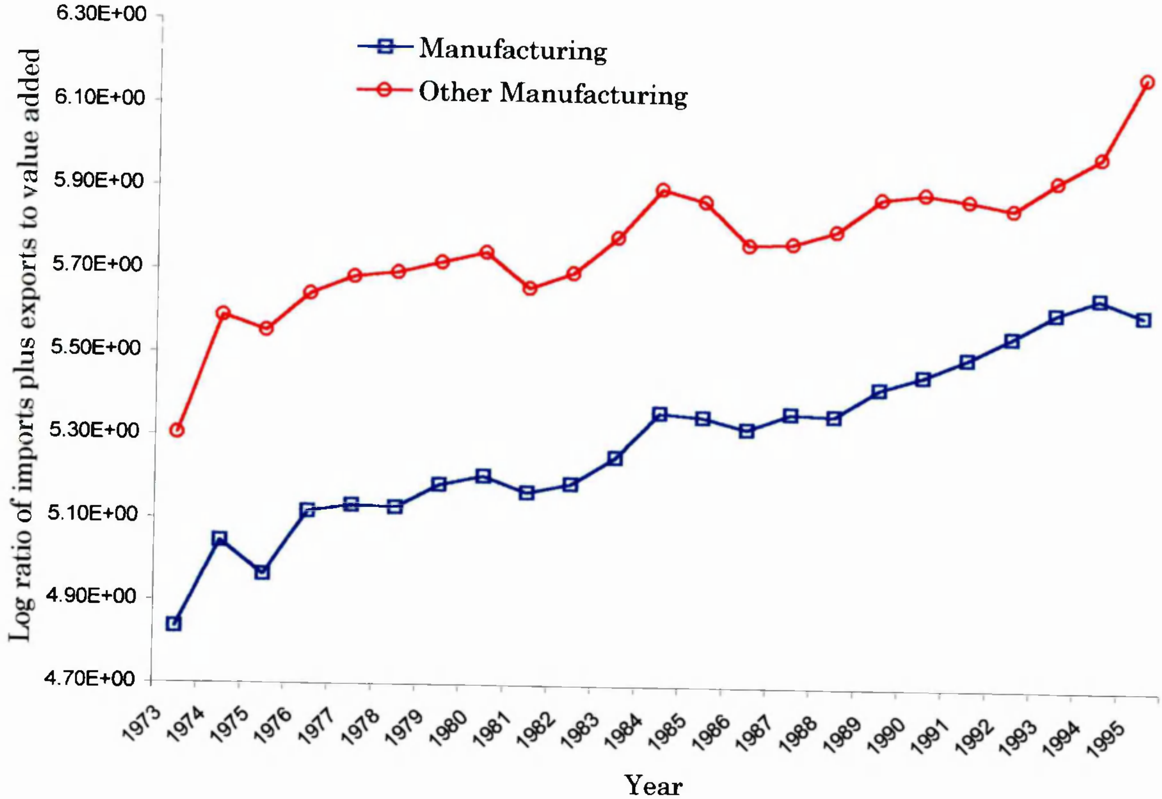


Figure A9 Trade intensity



A3 Industry matching following definition changes

The following table shows the results of testing the consistency of the data, following its matching as given in the main text (Chapter Five, section 5.2.4, Table 5.3). The detailed SIC definitions are shown below in Appendix 4. Those industry's which do not satisfy the criteria are where the statistic in *8081* is outweighed at least once by another year. Thus the only industry's passing the test excluding agriculture, are Manufacturing (SIC3), Other Manufacturing (SIC4), Construction (SIC5) and Transport & Communication (SIC7).

Table A3 Matching of industry categories

	SIC0	*SIC1*	*SIC2*	*SIC3*	*SIC4*	*SIC5*	*SIC6*	*SIC7*	*SIC8*	*SIC9*
7374	-4.55705	-7.21311	1.045296	4.825378	0.541696	3.098764	1.389685	-2.66889	0.314999	-5.53543
7475	20.74616	5.076453	-13.3451	-2.30811	7.983374	-4.82042	0.631992	-4.27295	-5.44482	-0.63913
7576	-1.09987	-1.61082	7.50233	2.577241	-4.76636	3.171025	-0.52635	1.277657	0.253573	-1.67428
7677	-11.4883	7.41915	5.356843	-0.87919	5.553078	1.443427	-1.78896	2.982955	-5.1768	-1.91514
7778	9.71897	3.972603	0.195174	-5.12022	1.330185	-1.16535	1.589626	-2.83065	-3.38387	0.643266
7879	-6.96066	-5.63481	-0.65778	2.050485	1.826739	8.001245	-3.19068	-2.23066	-0.29756	1.478385
7980	-5.53759	5.874409	2.666902	5.857013	1.462582	-9.9154	-0.37639	3.822346	-2.331	-2.58201
8081	**6.549215**	**-129.914**	**32.66195**	**4.270691**	**-3.00981**	**2.44766**	**28.05677**	**1.319389**	**-38.2895**	**-33.9218**
8182	-0.36885	1.716069	2.398275	-0.56184	-2.56164	4.276472	-1.11062	7.190608	4.447439	-1.99247
8283	-2.57248	2.063492	1.46328	0.683789	-1.94349	-2.32443	2.13422	3.882642	-4.45071	-0.46531
8384	-9.95223	10.47002	8.545811	5.541562	7.051527	-4.12438	-6.65059	0.731128	-8.02701	0.521963
8485	17.99421	-1.66546	-9.06863	3.422222	13.39374	-17.0354	6.14355	-14.0306	-17.9306	-1.26372
8586	8.830022	13.24786	19.32584	0.064427	10.38615	-2.71021	-8.82266	6.604231	-2.70875	-1.96679
8687	-25.1332	5.788177	-16.156	4.650949	-3.56612	1.917879	6.03308	1.573306	-14.6772	1.349127
8788	15.24768	3.137255	9.86211	-2.28919	1.526952	-9.59318	2.813447	-10.3812	-10.219	3.812529
8889	14.74886	8.77193	-11.0076	-0.04721	3.70486	3.520536	-1.90024	2.768937	-0.2903	-2.2213
8990	-24.9063	-12.8698	8.238466	3.001416	2.291149	3.773117	3.739316	-1.83306	-8.70194	-0.29146
9091	14.27959	18.17388	-0.88149	2.354773	-7.56553	-1.81865	-2.31056	-0.41787	6.565699	-1.63331
9192	8.054027	0.05339	-5.14563	0.36871	10.35476	0.038004	9.857002	-5.52177	-2.46705	-8.78819
9293	7.34494	2.831197	9.264389	1.05021	2.85616	8.46534	-14.1677	8.114667	2.016515	1.041389
9394	-4.99119	-1.81418	2.272727	4.144344	-1.09812	4.471826	0.857649	-7.93991	6.659274	-3.48653

A4 Decomposition of one digit industries (excluding agriculture)

Matched SIC 1 codes

(1) Pre - 1981

Coal and petroleum products (4)

Mineral oil refining

Gas, electricity and water (18)

Gas

Electricity

Water Supply

(2) Post - 1981

Energy and water supply industries (1)

Coal and Coke

Coal extraction and manufacture of solid fuels

- Deep coal mines
- Underground workers

Mineral oil processing

- Mineral oil refining

Other energy and water supply

Production and distribution of electricity, gas and other forms of energy

- Production and distribution of electricity
- Public gas supply

Water supply industry

Matched SIC 2 codes

(1) Pre - 1981

Mining and quarrying (2)

Coal mining

Chalk, clay, sand and gravel extraction

Chemicals and allied industries (5)

General chemicals

Pharmaceutical chemicals and preparations

Synthetic resins and plastics materials and synthetic rubber

Other chemical industries

Metal Manufacture (6)

Iron and Steel

- Iron and steel general (general)
- Steel tubes
- Iron castings etc..

Other Metals

- Aluminium and aluminium alloys
- Copper, brass and other copper alloys
- Other base metals

Bricks, pottery, glass, cement, etc. (13)

Bricks, fireclay and refractory goods

Pottery

Glass

Abrasives and building materials, etc.

(2) Post - 1981

Extraction of minerals and ores other than fuels, manufacture of metals, mineral products and chemicals (2)

Metals

Metal manufacturing

- Iron and steel industry
- Steel tubes
- Drawing, cold rolling and cold forming of steel
- Non-ferrous metals industry
    - *Aluminium and aluminium alloys*

Other mineral and mineral products

Extraction of minerals, not elsewhere specified

- Extraction of stone, clay, sand and gravel

Manufacture of non-metallic mineral products

- Structural clay products
- Building products of concrete, cement or plaster
  - *Other building products of concrete, cement or plaster*
- Glass and glassware
  - *Flat glass*
  - *Other glass products*
- Refractory and ceramic goods
  - *Ceramic goods*

Chemical industry

- Basic industrial chemicals except industrial gases
  - *Inorganic chemicals except specialised pharmaceutical chemicals*
  - *Synthetic resins and plastics materials*
  - *Dyestuffs and pigments*
- Paints, varnishes and printing ink
  - *Paints, varnishes and painters' fillings*
- Specialised chemical products mainly for industrial and agriculture
  - *Miscellaneous chemical products for industrial use*
- Pharmaceutical products
- Soap and toilet preparations

Matched SIC 3 codes

(1) Pre - 1981

Mechanical engineering (7)

Metal-working machine tools

Pumps, valves and compressors

Industrial engines

Textile machinery and accessories

Construction and earth-moving equipment

Mechanical handling equipment

Office machinery

Other machinery

Industrial (including process) plant and steelworks

Other mechanical engineering

Electrical engineering (7)

Electrical machinery

Insulated wires and cables

Telegraph and telephone apparatus and equipment

Radio and electronic compressors

Radio, radar and electronic capital goods

Electric appliances primarily for domestic use

Other electrical goods

Vehicles (7)

Wheeled tractor manufacturing

Motor vehicle manufacturing

Aerospace equipment manufacturing and repairing

Locomotives and railway track equipment

Railway carriages and wagons and trains

Instrument engineering (8)

Scientific and industrial instruments and systems

Shipbuilding and marine engineering (9)

(2) Post - 1981

Metal goods, engineering and vehicles industries (3)

Manufacture of metal goods not elsewhere specified

- Foundries
  - *Ferrous metal foundries*
  - *Non-ferrous foundries*
- Forging, pressing and stamping

•Bolts, nuts, etc., springs, non precision chains and metals treatment

- *Bolts, nuts, washers, rivets, springs and non-precision chains*
- *Heat and surface treatment of metals, including sintering*

•Metal doors, windows, etc.

•Hand tools and finished metal goods

- *Hand tools and implements*
- *Packaging products of metal*
- *Finished metal products, not elsewhere specified*

Mechanical engineering

•Industrial plant and steelworks

- *Fabricated constructional steelworks*
- *Boilers and process plant fabrications*

•Metal working machine tools and engineers ' tools

- *Metal working machine tools*
- *Engineers' small tools*

•Machinery for the food, chemical related industries

- *Food, drink and tobacco processing machinery, packaging and bottling machinery*
- *Process engineering contractors*

•Mining machinery, construction and mechanical handling equipment

- *Mechanical handling equipment*

•Mechanical power transmission equipment

- *Precision chains and other mechanical power transmission equipment*

•Machinery for the printing, paper, wood, leather, rubber, glass and related industries; laundry and dry cleaning machinery

- *Machinery for working wood, rubber, plastics, leather making, paper, glass, bricks and similar materials, laundry and dry cleaning machinery*

•Other machinery and mechanical equipment

- *Internal combustion engines (except for road vehicles, wheeled* *tractors primarily for agricultural purposes and aircraft) and other prime movers*

- *Compressors and fluid power equipment*
- *Refrigerating machinery, space heating, ventilating and air conditioning equipment*
- *Other industrial and commercial machinery*
- *Mechanical, marine and precision engineering*

Electrical engineering, etc.

Manufacture of office machinery and data processing equipment

- Electronic data processing equipment

Electrical and electronic engineering

- Insulated wires and cables
- Basic electrical equipment
- Electrical equipment for industrial use, batteries and accumulators
    - *Alarms and signalling equipment*
    - *Electrical equipment for industrial use not elsewhere specified*
- Telecommunications equipment, electrical measuring equipment, electronic capital goods and passive electronic components
    - *Electrical instruments and control systems*
    - *Radio and electronic capital goods*
    - *Components other than active components, mainly electronics*
- Other electronic equipment
    - *Electronic consumer goods and other electronic equipment*
- Domestic-type electric appliances
- Electrical equipment installation

Manufacture of motor vehicles and parts thereof

- Motor vehicles and their engines
- Motor vehicle bodies, trailers and caravans
    - *Motor vehicle bodies*
- Motor vehicle parts

Manufacturing of other transport equipment

- Shipbuilding and repairing
- Railway and tramway vehicles
- Aerospace equipment manufacturing and repairing

Instrument engineering

- Measuring, checking and precision instruments and apparatus
- Medical and surgical equipment and orthopaedic appliances

Matched SIC 4 codes

(1) Pre - 1981

Food, drink and tobacco (3)

Food

- Grain milling
- Bread and flour confectionery
- Biscuits
- Bacon curing, meat and fish products
- Milk and milk products
- Cocoa, chocolate and sugar confectionery
- Fruit and vegetable products
- Animal and poultry products

Drink

- Brewing and malting

Textiles (10)

Production of man made fibres

Spinning and doubling on the cotton and flax systems

Weaving of cotton, linen and man made fibres

Woollen and worsted

Hosiery and knitted goods

Carpets

Textile finishing

Other textile industries

Leather, leather goods and fur (11)

Clothing and footwear (12)

Clothing

•Men's and boys' tailored outerwear

Footwear

Timber, furniture, etc. (14)

Timber

Furniture and upholstery

Shop and office fitting

Paper, printing and publishing (15)

Paper, etc.

•Paper and board

•Packaging products of paper, board and associated materials

Printing and publishing

•Printing, publishing of newspapers

•Printing, publishing of periodicals

•Other printing, publishing, bookbinding, engraving, etc.

Other Manufacturing Industries (16)

Rubber

Plastic products n.e.s

(2) Post - 1981

Other manufacturing industries (4)

Food, drink and tobacco

•Food

•Slaughtering of animals and production of meat and by-products

- *Slaughter houses*
- *Bacon curing and meat processing*
- *Poultry slaughter and processing*

•Preparation of milk and milk products

•Processing of fruit and vegetables

•Bread, biscuits and flour

•Bread, biscuits and flour confectionery

- *Bread and flour confectionery*

•Ice cream, cocoa, chocolate and sugar confectionery

•Miscellaneous foods

•Drink and tobacco

•Brewing and malting

Textile industry

•Woollen and worsted industry

•Hosiery and other knitted goods

- *Hosiery and other weft knitted goods and fabrics*

•Textile finishing

•Carpets and other textile floor coverings

- *Pile carpets, carpeting and rugs*

•Miscellaneous textiles

Footwear, clothing and leather

Footwear and clothing industries

•Footwear

•Clothing, hats and gloves

•Household textiles and made-up textiles

Timber and woollen furniture industries

•Builders, carpentry and joinery

•Wooden and upholstered furniture and shop and office fittings

- *Wooden and upholstered furniture*

- *Shop and office fitting*

Manufacturing of paper and paper products; printing and publishing

•Manufacture of paper and paper products

•Pulp, paper and board

- Conversion of paper and board
    - *Packaging products of board*
    - *Other paper and board products*
- Printing and publishing
    - *Printing and publishing of newspapers*
    - *Other printing and publishing*

Processing of rubber and plastics

- Rubber products
    - *Rubber tyres and inner tubes*
    - *Other rubber products*
- Processing of plastics
    - *Plastics semi-manufacture*
    - *Plastics building products*
    - *Plastic packaging products*
    - *Plastics products not elsewhere specified*

Other manufacturing products

Matched SIC 5 codes

(1) Pre - 1981

Construction (17)

(2) Post - 1981

Construction (5)

General construction and demolition work

Construction and repair of buildings

Civil engineering

Installation of fixtures and fittings

Building completion work

Matched SIC 6 codes

(1) Pre - 1981

Distribution trades [wholesale - retail] (20)

Wholesale distribution

- Wholesale distribution of food and drink
- Wholesale distribution of petroleum products

Retail distribution

- Retail distribution of food and drink
- Other retail distribution

Dealing in coal, oil, builders' materials, grain and agricultural supplies

Dealing in other industrial materials and machinery

Miscellaneous services (23)

Cinemas, theatres, radio etc.

Catering

- Hotels and other residential establishments
- Restaurants, cafes, snack bars

Motor repairers, distributors, garages and filling stations

Other services

(2) Post - 1981

Distribution, hotels and catering, repairs (6)

Wholesale distribution and commission agents

Wholesale distribution (except dealing in scrap and waste materials)

- Wholesale distribution of fuels, ores, metals and industrial materials
- Wholesale distribution of timber and building materials
- Wholesale distribution of machinery, industrial and transport
  - *Wholesale distribution of machinery, industrial and transport equipment other than motor vehicles*
- Wholesale distribution of food, drink and tobacco
- Other wholesale distribution including general wholesalers

Dealing in scrap and waste materials

Retail distribution

- •Food retailing
- •Retail distribution of household goods, hardware and ironmongery
- •Retail distribution of motor vehicles and parts
- •Other specialised retail distribution (non-food)
- •Mixed retail businesses

Hotels and catering

- •Restaurants, snack bars, cafes and other eating places
    - *Eating places supplying food for consumption on the premises*
- •Public houses and bars
- •Canteens and messes
- •Hotel trade

Repair of consumer goods and vehicles

- •Repair and servicing of motor vehicles

Matched SIC 7 codes

(1) Pre - 1981

Transport and communication (19)

Railways

Road passenger transport

Road haulage contracting for general hire or reward

Sea transport

Port and inland water transport

Air transport

Postal services and telecommunications

Miscellaneous transport services and storage

(2) Post - 1981

Transport and communication (7)

Railways

Other inland transport

- Scheduled road passenger transport and urban railways
- Road haulage

Air transport

Supporting services to transport

- Supporting services to inland transport
- Supporting services to sea transport
- Supporting services to air transport

Miscellaneous transport services and storage not elsewhere specified

Postal services and telecommunications

- Postal services
- Telecommunications

Matched SIC 8 codes

(1) Pre - 1981

Insurance, banking finance and business services (21)

Banking and bill discounting

Property owning and managing etc.

(2) Post - 1981

Banking, finance, insurance, business services and leasing (8)

Banking and finance

Business services

- Professional and technical services not elsewhere specified
- Business services
    - *Computer services*
    - *Business services, not elsewhere specified*

Renting of movables

- Hiring out construction machinery and equipment
- Hiring out consumer goods
- Hiring out transport equipment

•Hiring out other movables

Owning and dealing in real estate

Matched SIC 9 codes

(1) Pre - 1981

Professional and scientific services (22)

Educational services

Medical and dental services

Research and development services

Public administration and defence (24)

National government service

Local government service

(2) Post - 1981

Other services (9)

Public administration, national defence and compulsory security

•National and local government services not elsewhere specified

- National government service not specified elsewhere

- Local government service not elsewhere specified

Miscellaneous services

Sanitary services

•Refuse disposal, sanitation and similar services

- Refuse disposal, street cleaning, fumigation, etc.

•Cleaning services

Professional and scientific services

Education

•Higher education

•School education (nursery, primary and secondary)

•Education not elsewhere specified and vocational training

Medical and other health services : veterinary services

- Hospitals, nursing homes, etc.
- Other medical care institutions

Other services provided to the general public

- Social welfare, charitable and community services

Recreational services and other cultural services

- Libraries, museums, art galleries, etc.
- Sport and other recreational services

Personal services

- Laundries, dyers and dry service

A5 Plots of outliers from stage one of the procedure

The following figures (A10 to A25) show the residual from the estimated earnings function, for each industry. Any outliers which are present are identified. This is important, because outliers will influence the measure of within-group earnings dispersion. All the results of the second stage were estimated after correcting for outliers in the residuals.

Figure A10 Distribution of residuals in Manufacturing in 1992

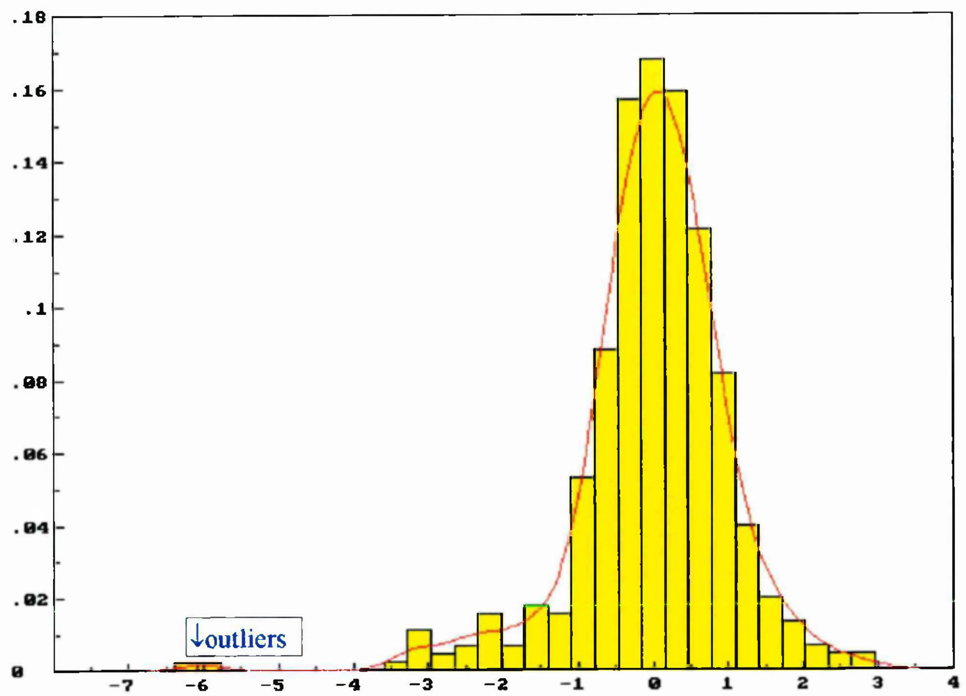


Figure A11 Distribution of residuals in Manufacturing in 1993

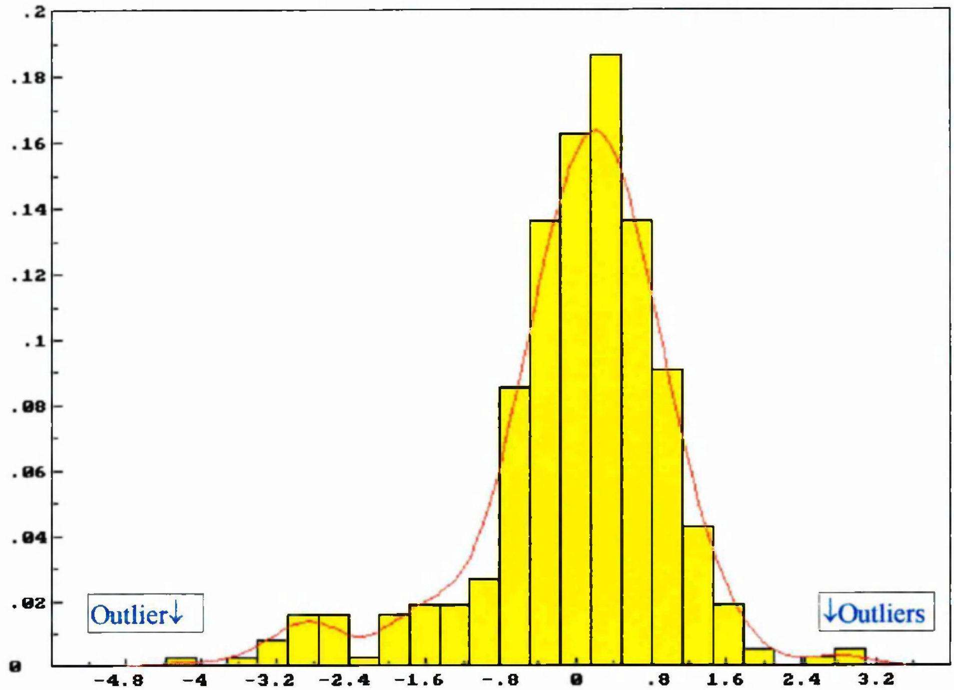


Figure A12 Distribution of residuals in Manufacturing in 1994

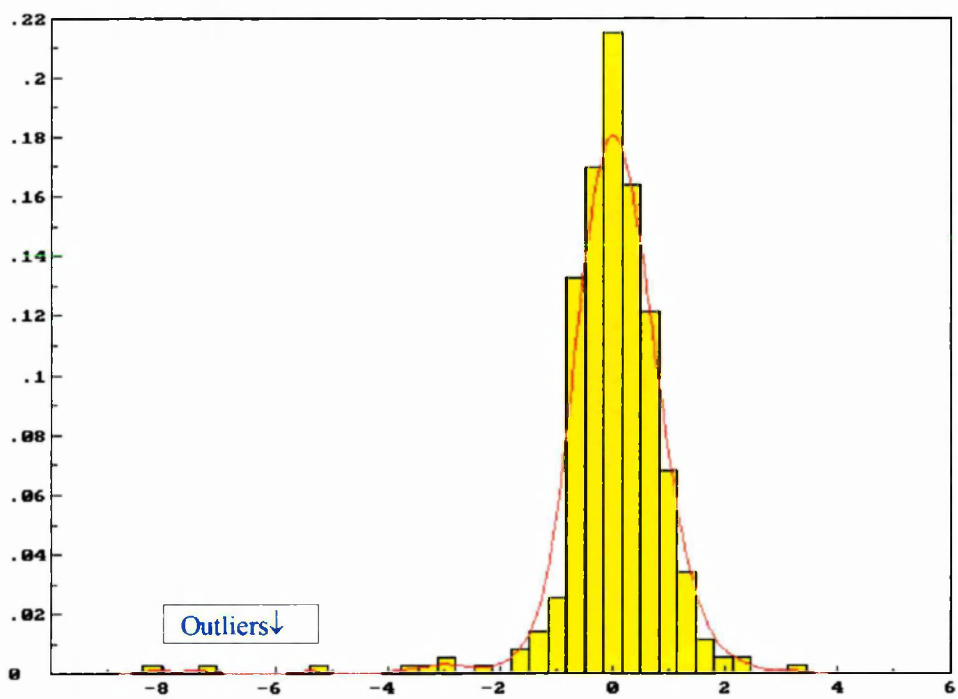


Figure A13 Distribution of residuals in Manufacturing in 1995

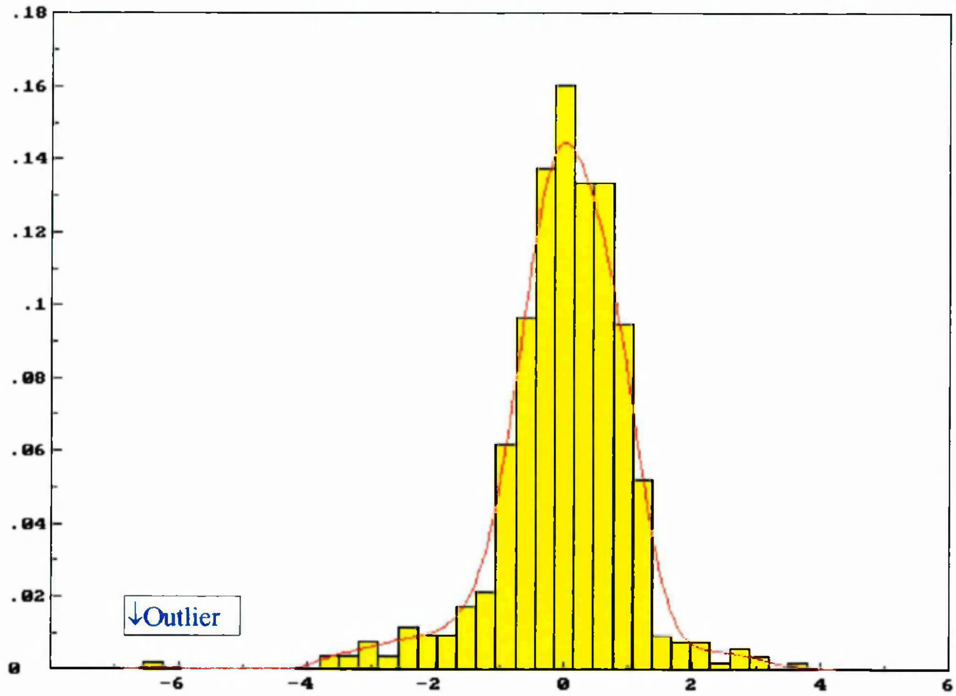


Figure A14 Distribution of residuals in Other Manufacturing in 1992

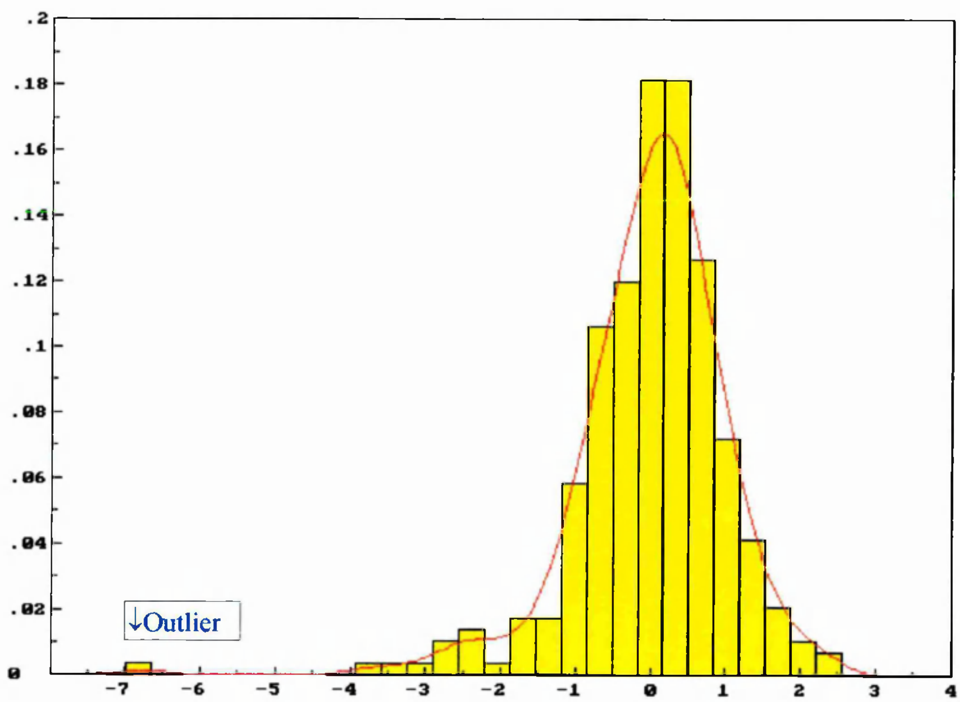


Figure A15 Distribution of residuals in Other Manufacturing in 1993

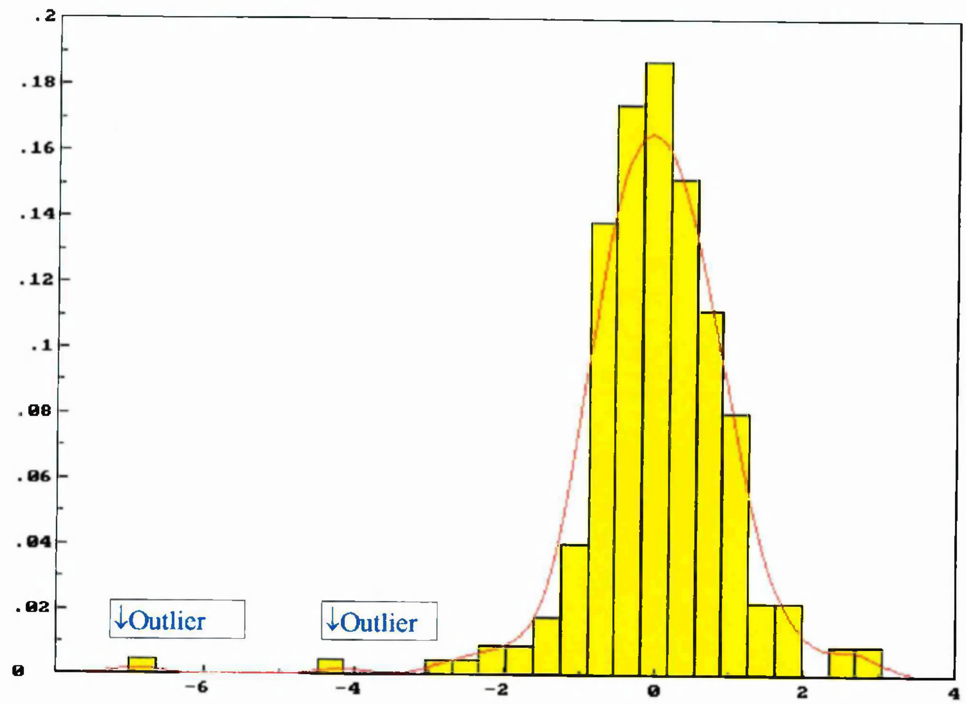


Figure A16 Distribution of residuals in Other Manufacturing in 1994

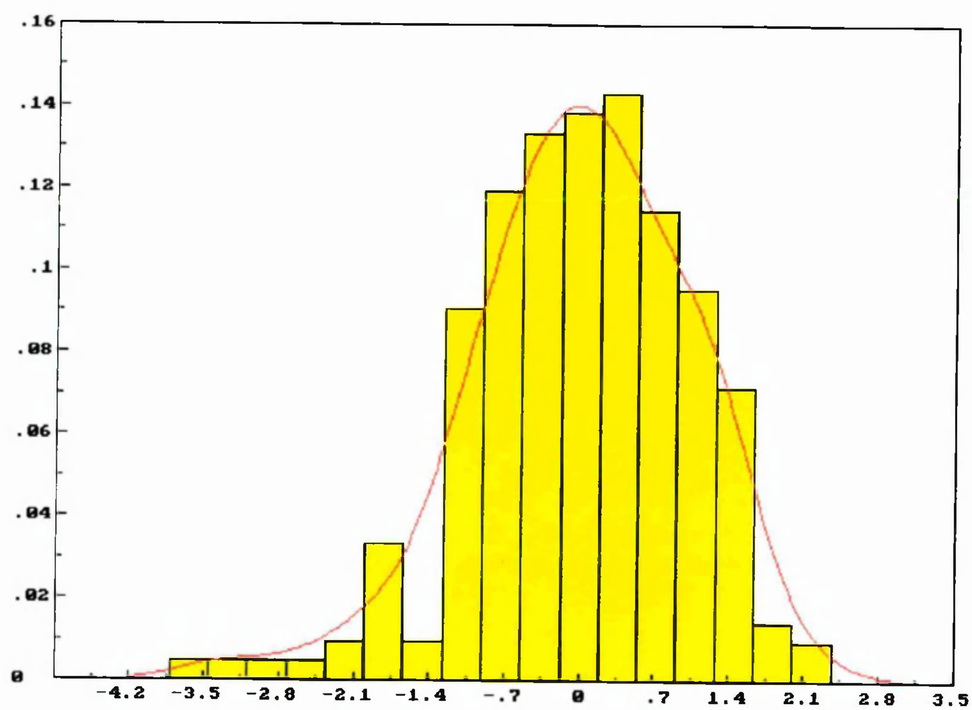


Figure A17 Distribution of residuals in Other Manufacturing in 1995

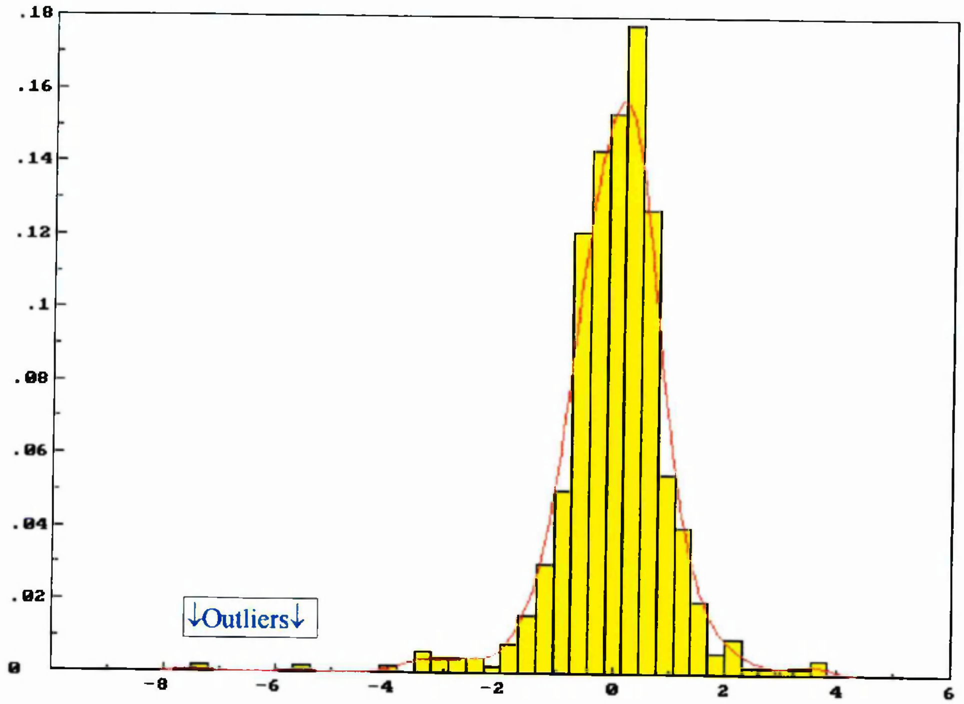


Figure A18 Distribution of residuals in Construction in 1992

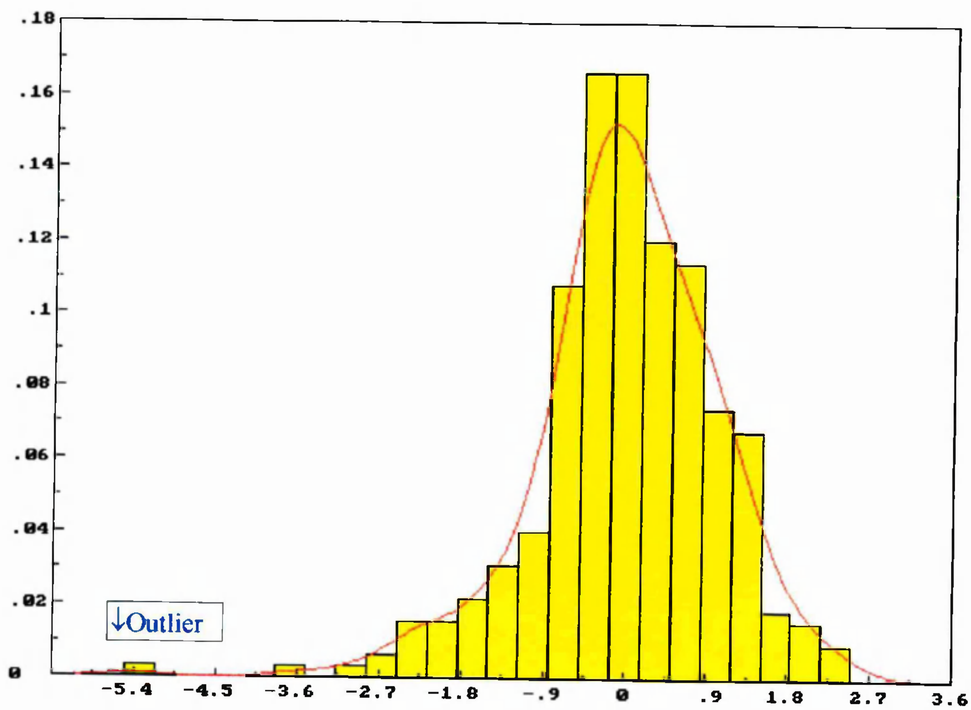


Figure A19 Distribution of residuals in Construction in 1993

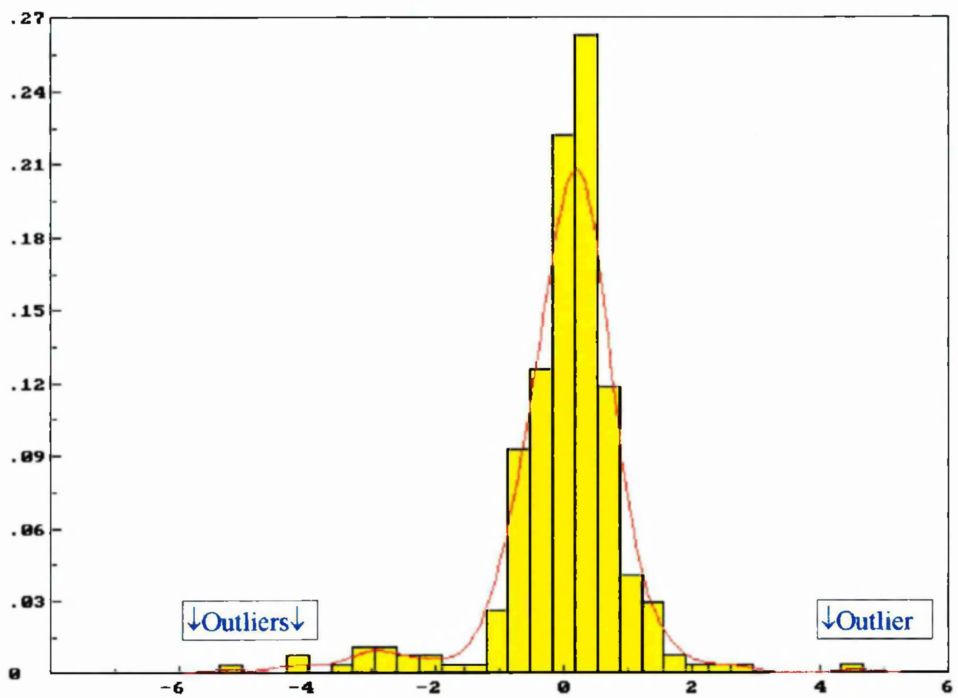


Figure A20 Distribution of residuals in Construction in 1994

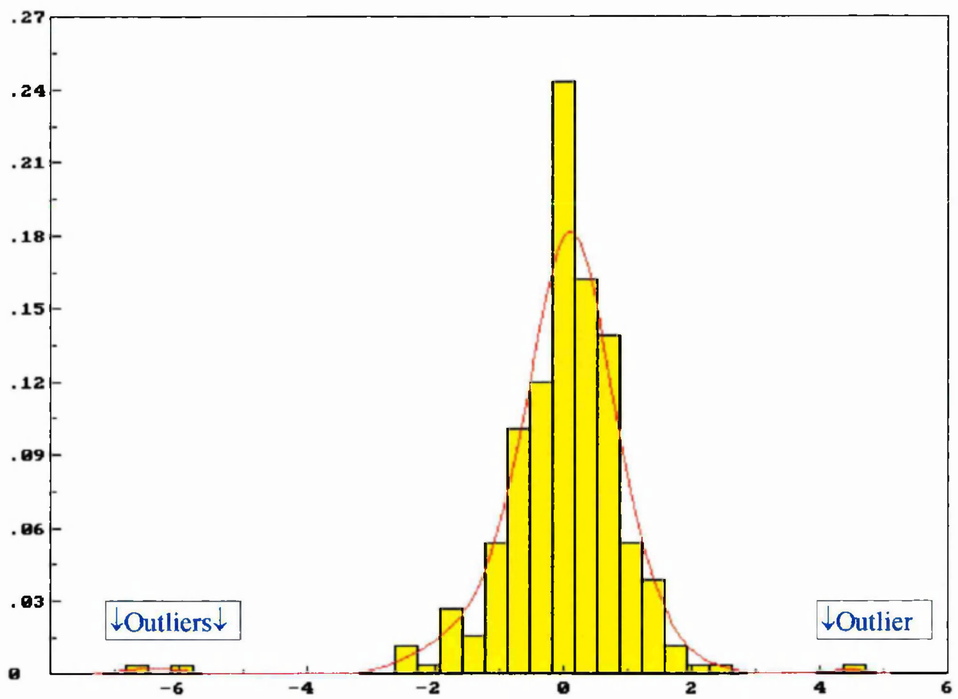


Figure A21 Distribution of residuals in Construction in 1995

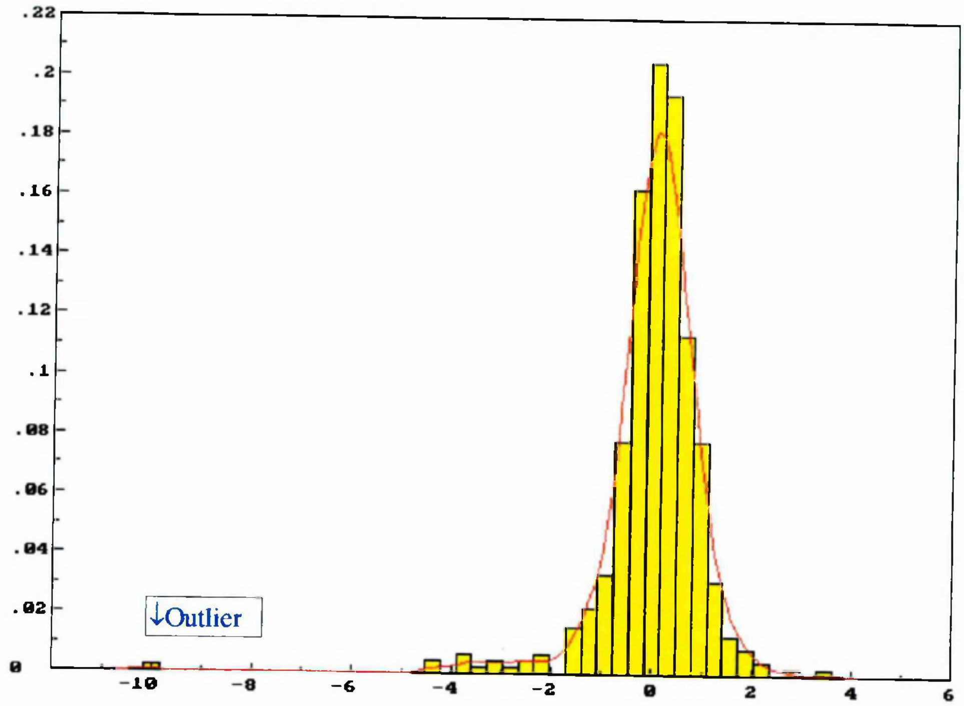


Figure A22 Distribution of residuals in Transport and Communication in 1992

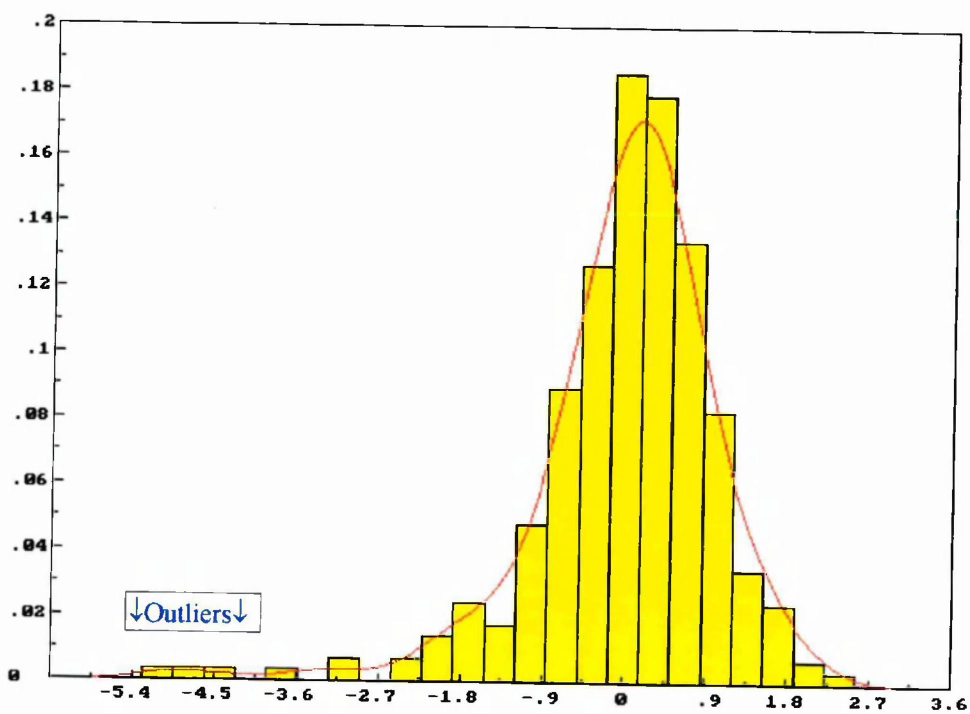


Figure A23 Distribution of residuals in Transport and Communication in 1993

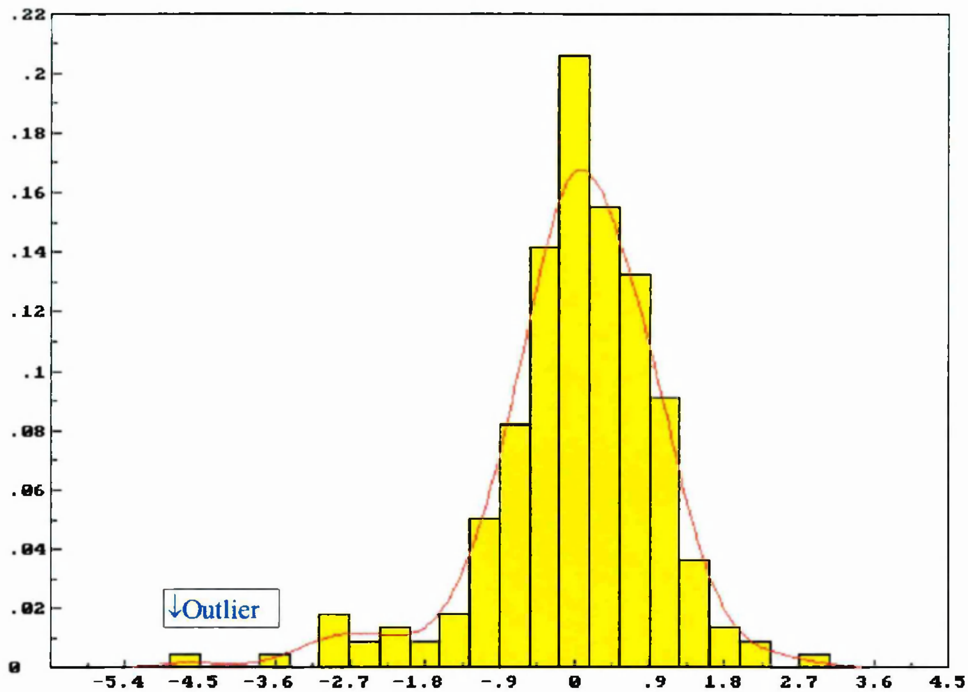


Figure A24 Distribution of residuals in Transport and Communication in 1994

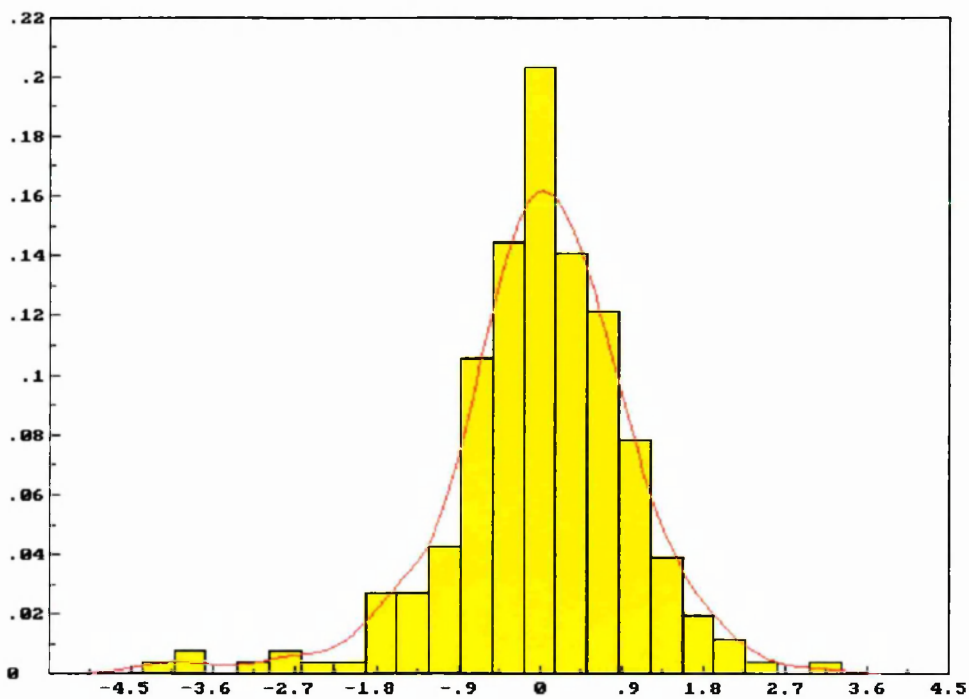
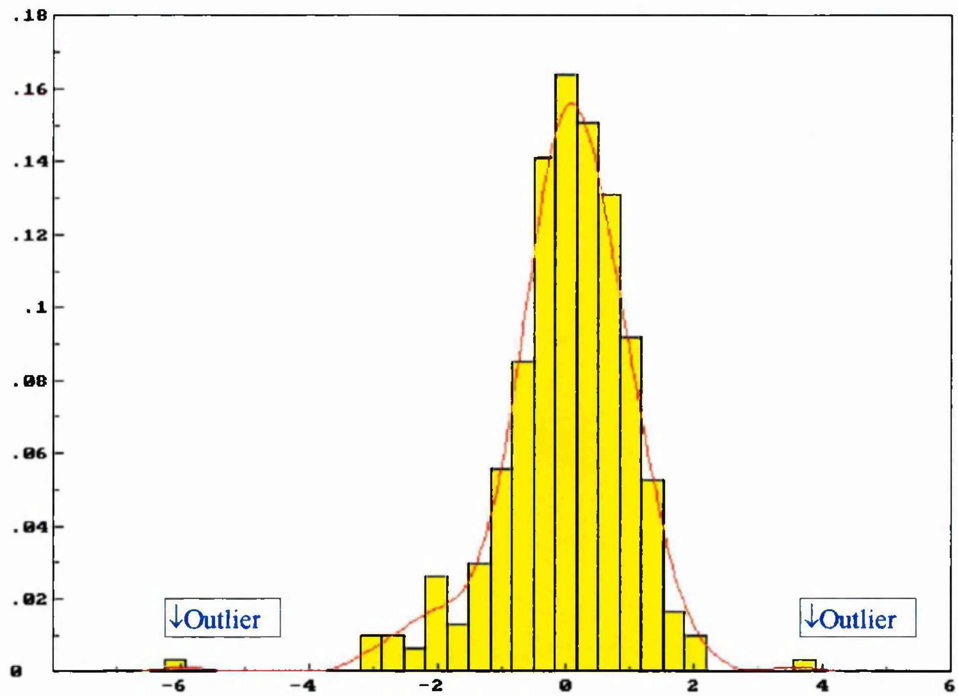


Figure A25 Distribution of residuals in Transport and Communication in 1995



A6 Industry data used in the second stage

Table A4 The number of workers involved in strike activity

	Manufacturing	Other Manufacturing	Construction	Transport and Communication
1973	989,198	26,099	28,500	147,100
1974	1,013,105	8,099	22,400	135,099
1975	627,701	4,500	26,299	81,700
1976	487,599	27,799	51,500	42,699
1977	856,903	20,500	34,199	56,700
1978	698,401	5,499	39,000	97,500
1979	2,236,807	9,699	30,180	249,598
1980	456,201	1,800	30,299	99,000
1981	499,498	4,000	12,300	94,099
1982	804,398	52,500	10,500	481,301
1983	284,099	37,500	6,900	47,600
1984	515,498	6,399	17,300	191,800
1985	214,299	5,200	5,499	103,899
1986	194,500	2,200	7,700	71,899
1987	202,199	1,499	3,799	206,800
1988	175,299	1,999	4,000	321,399
1989	117,699	9,800	20,100	112,300
1990	108,800	1,200	4,500	68,200
1991	51,500	2,400	6,200	11,700
1992	25,600	6,300	3,900	6,499
1993	29,999	16,813	999	71,000
1994	100	23,000	1,974	1,000
1995	400	32,800	2,000	200

Table A5 Research and development intensity – R&D expenditure as a percentage of value added

	Manufacturing	Other Manufacturing	Construction	Transport and Communication
1973	6.45	0.82	0.83	6.27
1974	6.68	0.97	0.87	6.17
1975	6.31	0.98	0.91	5.91
1976	6.89	0.99	0.95	6.53
1977	6.65	0.94	1.00	7.73
1978	6.88	0.90	0.89	7.75
1979	8.19	0.85	1.01	6.57
1980	8.88	0.79	1.06	5.44
1981	9.79	0.74	1.18	4.34
1982	9.50	0.64	1.12	3.50
1983	9.22	0.61	0.99	2.79
1984	9.50	0.69	0.92	2.31
1985	9.39	0.72	1.16	2.59
1986	8.88	0.65	1.31	7.42
1987	8.74	0.59	1.08	7.30
1988	8.60	0.51	1.07	6.42
1989	8.70	0.64	0.88	6.73
1990	9.31	0.67	0.55	6.46
1991	9.60	0.65	0.60	6.41
1992	10.16	0.65	0.50	6.02
1993	10.18	0.69	0.38	6.34
1994	9.80	0.71	0.35	6.49
1995	8.66	0.64	0.13	6.67

Table A6 Percentage of females in the labour force

	Manufacturing	Other Manufacturing	Construction	Transport and Communication
1973	24.85	46.39	5.56	19.80
1974	25.47	41.61	8.79	19.00
1975	24.56	44.69	6.91	20.13
1976	23.34	44.37	8.10	18.61
1977	22.76	44.96	9.57	19.58
1978	23.23	42.96	9.45	18.40
1979	23.63	45.87	9.73	20.53
1980	23.76	44.02	9.27	20.64
1981	20.28	44.38	9.67	23.22
1982	19.68	43.58	10.22	25.81
1983	16.43	37.13	7.97	16.35
1984	20.05	33.53	8.49	17.77
1985	20.10	35.71	8.28	17.06
1986	16.80	36.29	9.14	18.20
1987	18.28	36.42	10.71	19.17
1988	20.98	34.66	7.82	22.89
1989	18.42	40.88	13.07	24.09
1990	18.74	38.18	14.81	21.68
1991	22.84	33.58	13.52	18.71
1992	21.52	34.53	15.64	22.74
1993	21.66	38.32	16.03	23.17
1994	22.06	42.81	17.32	21.41
1995	21.46	38.82	7.66	24.55

Table A7 Percentage of immigrants in the labour force

	Manufacturing	Other Manufacturing	Construction	Transport and Communication
1973	7.81	8.31	7.59	7.87
1974	7.91	7.76	5.94	5.13
1975	5.57	7.25	5.13	7.13
1976	7.02	6.45	4.81	5.99
1977	7.12	8.25	6.38	7.18
1978	9.99	7.75	6.72	7.89
1979	7.24	8.72	5.99	7.93
1980	7.31	9.19	7.61	8.97
1981	7.78	7.82	3.93	9.21
1982	7.65	7.78	4.49	7.40
1983	6.46	8.59	7.69	10.82
1984	7.71	7.93	5.21	8.75
1985	5.29	7.45	5.92	6.64
1986	5.44	9.52	5.89	6.15
1987	6.09	7.46	2.98	8.55
1988	7.16	6.13	5.31	8.19
1989	4.20	6.32	4.77	7.53
1990	5.61	5.10	4.01	7.08
1991	5.31	5.85	4.23	8.69
1992	5.06	7.69	4.59	6.32
1993	6.74	6.24	4.88	8.26
1994	5.81	7.73	7.09	8.88
1995	6.74	7.02	4.67	6.59

Table A8 Trade Intensity – export plus import expenditure as a percentage of value added

	Manufacturing	Other Manufacturing
1973	125.96	201.10
1974	155.02	266.99
1975	143.17	257.60
1976	166.81	281.90
1977	169.30	293.71
1978	168.68	297.18
1979	178.25	304.44
1980	182.16	311.86
1981	175.12	286.46
1982	178.91	297.28
1983	191.04	324.35
1984	212.72	364.35
1985	210.92	354.21
1986	205.14	319.30
1987	213.13	320.67
1988	212.06	331.00
1989	226.83	358.06
1990	233.80	362.16
1991	244.08	356.73
1992	257.25	349.75
1993	272.80	374.40
1994	283.15	396.61
1995	271.80	480.91

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